1989

Sixth Fleet Combat Stores ship resupply model

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http://hdl.handle.net/10945/27269

NAVAL POSTGRADUATE SCHOOL
Monterey, California

THESIS

SIXTH FLEET COMBAT STORES SHIP
RESUPPLY MODEL

by

Jeffery P. Bennett

March 1989

Thesis Advisor: David R. Henderson

Unclassified

security classification of this page

REPORT DOCUMENTATION PAGE

1a Report Security Classification Unclassified	1b Restrictive Markings
2a Security Classification Authority	3 Distribution Availability of Report Approved for public release; distribution is unlimited.
2b Declassification Downgrading Schedule	
4 Performing Organization Report Number(s)	5 Monitoring Organization Report Number(s)
6a Name of Performing Organization Naval Postgraduate School — 6b Office Symbol *(if applicable)* 54	7a Name of Monitoring Organization Naval Postgraduate School
6c Address *(city, state, and ZIP code)* Monterey, CA 93943-5000	7b Address *(city, state, and ZIP code)* Monterey, CA 93943-5000
8a Name of Funding Sponsoring Organization — 8b Office Symbol *(if applicable)*	9 Procurement Instrument Identification Number
8c Address *(city, state, and ZIP code)*	10 Source of Funding Numbers: Program Element No — Project No — Task No — Work Unit Accession No

11 Title *(Include security classification)* SIXTH FLEET COMBAT STORES SHIP RESUPPLY MODEL

12 Personal Author(s) Jeffery P. Bennett

13a Type of Report	13b Time Covered	14 Date of Report *(year, month, day)*	15 Page Count
Master's Thesis	From To	March 1989	77

16 Supplementary Notation The views expressed in this thesis are those of the author and do not reflect the official policy or position of the Department of Defense or the U.S. Government.

17 Cosati Codes			18 Subject Terms *(continue on reverse if necessary and identify by block number)*
Field	Group	Subgroup	logistics, inventory, resupply, lognormal distribution

19 Abstract *(continue on reverse if necessary and identify by block number)*

This thesis improves the method of determining inventory levels for commodities (provisions, high usage load list consumables, and ships store merchandise) managed by the Sixth Fleet on station AFS. Historical demand generated by ships deployed to the Sixth Fleet is used to develop two models, the Lognormal Model and the Point Estimate Model. Improvement is achieved by considering each item's variance in demand. The Lognormal Model computes sample standard deviations for each item and provides the more accurate results. The Point Estimate Model uses regression to estimate a standard deviation for groups of items. Although the Point Estimate Model is easier for hands-on users to understand it is no easier to implement. The two models are compared against current procedures using a second set of actual Sixth Fleet data to simulate six months of inventory activity. Satisfied customer demands are improved by five percentage points (from 93% to 98%) and end of the month contingency inventory reserves are improved by 30 percentage points (from 65% to 95%).

20 Distribution Availability of Abstract ☒ unclassified unlimited ☐ same as report ☐ DTIC users	21 Abstract Security Classification Unclassified
22a Name of Responsible Individual David R. Henderson	22b Telephone *(include Area code)* (408) 646-2524 — 22c Office Symbol 54Ht

DD FORM 1473,84 MAR — 83 APR edition may be used until exhausted. All other editions are obsolete — security classification of this page

Unclassified

Sixth Fleet Combat Stores Ship Resupply Model

by

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Submitted in partial fulfillment of the
requirements for the degree of

MASTER OF SCIENCE IN OPERATIONS RESEARCH

from the

NAVAL POSTGRADUATE SCHOOL
March 1989

ABSTRACT

This thesis improves the method of determining inventory levels for commodities (provisions, high usage load list consumables, and ships store merchandise) managed by the Sixth Fleet on station AFS. Historical demand generated by ships deployed to the Sixth Fleet is used to develop two models, the Lognormal Model and the Point Estimate Model. Improvement is achieved by considering each item's variance in demand. The Lognormal Model computes sample standard deviations for each item and provides the more accurate results. The Point Estimate Model uses regression to estimate a standard deviation for groups of items. Although the Point Estimate Model is easier for hands-on users to understand it is no easier to implement. The two models are compared against current procedures using a second set of actual Sixth Fleet data to simulate six months of inventory activity. Satisfied customer demands are improved by five percentage points (from 93% to 98%) and end of the month contingency inventory reserves are improved by 30 percentage points (from 65% to 95%).

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I. INTRODUCTION

The Sixth Fleet (SIXTHFLT) on station Combat Stores ship (AFS/TAFS) is the inventory manager for the operating forces deployed to the Mediterranean. It must ensure that enough food, repair parts, and consumables are available to support continuous Fleet operations. In this capacity, the on station AFS/TAFS coordinates the logistics replenishment (LOGREP) plan which schedules, for every customer, a monthly resupply of provisions and stores from one of the Combat Logistics Force (CLF) ships.[1] Inventory levels for repair parts and for most consumables are determined by the Fleet Issue Load List (FILL) Model. The Fleet Material Support Office maintains the model and the Ships Parts Control Center applies the model quarterly to update inventory range and depth. Not supported by specific models are the inventory levels for provisions, High Usage Load List (HULL) consumables, and ship's store resale merchandise (QCOG). Management responsibility for these items belongs to the on station AFS TAFS.

For provisions and HULL items, Commander Naval Surface Force Atlantic Fleet (COMNAVSURFLANT) has established minimum support levels and recommended load quantities for each CLF ship. Load quantities are based on Sixth Fleet demand data and tailored to support a Naval task force of approximately 23,000 people. This support level is called a Load 1 and is published in COMNAVSURFLANT Notice 4423 [Ref. 1]. COMNAVSURFLANT Notice 4423 also establishes the following inventory policy for the commodities not supported by the FILL model:

> The on station AFS may call out additions or deletions to the above load plan as necessary to make sure that at least one month's SIXTHFLT Average Monthly Demand (AMD) is always on hand on board SIXTHFLT CLF ships and that a minimum amount of load material is returned to CONUS for turn in ashore.

This thesis identifies weaknesses in the current inventory management methodology used in the Sixth Fleet by the on station AFS for provisions, HULL, and QCOG. The analysis and design of alternative models, to better support the COMNAVSURFLANT inventory policy, uses historical Sixth Fleet demand. Improved inventory positions in

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1 Combat Logistic Force (CLF) ship types are AE, AFS, AO, AOE, AOR, TAFS, TAO, AND TAT(S).

these commodities will better support the Sixth Fleet. The alternative models evolve from the data analysis conducted on 22 months of Sixth Fleet demand data.

Chapter II provides background on the logistic support requirements for the forces deployed to the Sixth Fleet and an overview of the operating environment. Additionally, the two current inventory management methodologies are explained, followed by a discussion of associated management problems.

Chapter III describes the approach used in collecting, validating, and analyzing demand data and Chapter IV provides the results and application of the data analysis.

Chapter V outlines the development and application of two alternative models that compute monthly stocking objectives. The model development includes a discussion of the underlying assumptions and computational methods.

In Chapter VI the alternative models are compared to the current method of forecasting demand, using a data set generated by actual Sixth Fleet demand to simulate six LOGREP cycles. Chapter VII summarizes the thesis and presents recommendations for implementation.

II. BACKGROUND

A. SIXTH FLEET LOGISTICS REPLENISHMENT OPERATIONS

Executing the monthly LOGREP schedule requires effective planning and integrated coordination at every level. The Sixth Fleet staff determines operating objectives and the LOGREP schedule; the on station AFS determines CLF customer assignments and inventory distribution; CLF First Lieutenants determine along side line-ups[2] and rig transfer assignments; Cargo Officers determine material issue schedules and staging plans; Hold Captains determine work assignments and packaging requirements. These events depend on each other. Schedule changes are disruptive and frequent. The environment is dynamic.

Each ship deployed to the SIXTHFLT orders and receives a monthly resupply of provisions, consumable items, repair parts, and ship's store resale merchandise. The entire process, from customer ships submitting requirements to delivery ships replenishing depleted stocks, is repeated every month and called a cycle. While deployed to the Sixth Fleet, the on station AFS focuses most inventory management efforts on the 200 provision, 50 HULL and 130 QCOG items that the FILL model does not support.

The LOGREP process begins with the on station AFS receiving customer requirements and then assigning each customer a delivery platform. Delivery platforms must then have their inventory loads adjusted based on customer requirements. With Sixth Fleet ships dispersed throughout the Mediterranean, the multiple delivery platforms must be flexible to complete services to all customers. Dispersion of forces also disperses CLF ships. Beginning inventories on delivery ships must support initial customer assignments and provide some level of contingency for additional customers that result from schedule changes. Unplanned load adjustments in mid-cycle are difficult to achieve. Once a LOGREP cycle begins, the quantity of material in the Mediterranean does not increase until an end of the month resupply arrives.

Sixth Fleet provision, HULL, and QCOG inventory levels are scheduled to be replenished eight times a year. The resupply schedule, promulgated by COMNAVSURFLANT, is the basis for the material support pipeline. The process begins when initial reorders, called callouts, are submitted by the on station AFS to

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[2] I.e., how the ships line up for the station-to-station connected replenishment transfer.

Norfolk Naval Supply Center, 60 days prior to delivery. This requires predicting demand that will not occur for two to three months. A supplemental callout can be submitted 30 days later, after the next month's initial requirements are received from customer ships. All callouts are then loaded on either a resupply shuttle ship or, once every four months, on the relieving AFS. [Ref. 2: p. 31]

Chartered commercial carriers can be used to resupply items with insufficient inventories on those months when a resupply is not scheduled. Effective October 1, 1988, chartered commercial resupplies are no longer scheduled, planned events. Now the on station AFS requests a commercial resupply only when it projects that the inventory level for an item will not support the upcoming LOGREP cycle. While limiting the use of commercial resupplies saves money, a more difficult forecasting task is now assigned to the on station AFS. The period at risk for a forecasting decision is increased by 30 days when a resupply is not scheduled at the end of a LOGREP cycle.

Table 1. MAJOR EVENTS IN RESUPPLY PROCESS

	April	1	Receive April resupply
			Submit May supplemental callout to NSC Norfolk
		15	Submit June callout to NSC Norfolk
		25	Receive May requirements from customer ships
		30	Receive EOM inventories from CLF ships
RISK	May	1	Receive May resupply
			Submit June supplemental callout to NSC Norfolk
		25	Receive June requirements from customer ships
		31	Receive EOM inventories from CLF ships
	June	1	Receive June resupply
		15	Submit August callout to NSC Norfolk
		25	Receive July requirements from customer ships
		30	Receive EOM inventories from CLF ships
	July	1	No resupply scheduled
			Submit August supplemental callout to NSC Norfolk
		15	Submit September callout to NSC Norfolk
		25	Receive August requirements from customer ships
		31	Receive EOM inventories from CLF ships
	August	1	Receive August resupply

Table 1 outlines the major resupply events supporting LOGREP cycles and the length of time the inventory reorder decisions are at risk for the June callout. July is designated as one of the four months when a beginning of the month resupply is not scheduled. The inventory to meet July requirements is ordered in April and May, and received in June. That makes inventory decisions for the June callout at risk for three months, from 1 May to 31 July. Specifically, inventory levels for July can not be changed after items are ordered for the final time on the June supplemental callout that is submitted on 1 May.

Reorder quantities and subsequent inventory levels are constrained by total available space. Dry provisions and most HULL items can be stowed on deck; the availability of space on deck significantly increases total available storage space. Other commodities have specific storage requirements, and therefore, restrictive storage constraints. Included in this category are paint and flammable liquids requiring flammable storage, freeze and chill provisions requiring refrigerated storage, and ship's store merchandise requiring secure storage.

Space constraints make forecasting and safety stock determination into dynamic problems. The available space changes as various CLF ships rotate in and out of the Mediterranean. The current policy is for all provisions and ship's store merchandise to remain in theater, requiring the complete download of those inventories prior to each CLF ship's departure. This is usually done during a turnover period; however, resupply shuttle ships that assist for one or two cycles may not have a direct turnover with a replacement ship. Their departure results in a significant decrease in total storage capacity. Forecasting in this environment, to meet the COMNAVSURFLANT goal of maintaining at least one month AMD on hand at all times, involves both analysis of demand and tracking of CLF ship's schedules to determine current and projected storage capacities.

B. CURRENT METHODOLOGY

1. The Method

The current method used to achieve the COMNAVSURFLANT Notice 4423 inventory policy for provisions, HULL, and QCOG, is to set an inventory objective that will ensure that at least 2.1 times Average Monthly Demand (2.1 AMD) is on hand at the beginning of each month. When a scheduled resupply is to be received at completion of the LOGREP cycle, the month's beginning inventory objective is 2.1 AMD. When no resupply is scheduled at month's end, the beginning inventory objective is 3.1 AMD.

In theory, a 3.1 AMD inventory level at the beginning of a month will provide a 2.1 AMD inventory level at month's end and at least a one AMD inventory level after a second LOGREP cycle. This satisfies the COMNAVSURFLANT goal of one AMD on hand at all times. A 2.1 AMD level of beginning inventory has three components; support for the upcoming LOGREP cycle, a 30 day safety level in the event a planned resupply does not arrive, and a component to account for variance or spikes in demand.

Quantity	*Component*
1 AMD	Expected demand for next LOGREP cycle.
1 AMD	COMNAVSURFLANT one month safety level.
.1 AMD	Protection against variance in demand.

Success of a 2.1 AMD inventory depends, in part, on the accuracy of the AMD computation. The most common method for computing an AMD is to compute a simple average of demand over the past six to twelve months, even though 24 months historical demand is available from existing Shipboard Uniform Automated Data Processing (SUADPS) files. The stocking objective for the 2.1 AMD inventory level is:

$$\text{Stocking Objective } = 2.1 \times \sum_{t=1}^{n} \frac{D_{i,t}}{n} \qquad \text{for each i, where,} \qquad \{1\}$$

i	Item (i = 1,....,m), where m is the total number of items
t	Month (t = 1,....,n)
n	Number of months of historical demand in the baseline
$D_{i,t}$	Monthly demand for item i in month t

2. The Problems

Limiting the use of chartered commercial resupplies magnifies a problem that has always existed with this method of forecasting demand. The number of ships deployed to the Sixth Fleet is never a constant, and can range from 20 to 50 or more. This can cause a significant under- or over-estimate an of AMD, and can produce ineffective demand forecasts. When a resupply is not received at the end of a month this same and potentially inaccurate inventory must support Sixth Fleet units for an additional month.

Two shortcomings exist in the 2.1 AMD method. First is the inherent inaccuracies and variations of the baseline demand. The number of men supported during the collection of demand data is not guaranteed to equal the number during the next month.

However, this is the data used to calculate the AMD that supports the next month's activity. Recognizing this, the inventory manager often scales the AMD up (or down) if more (or fewer) customers are scheduled to be in theater than when the historical demand was generated. Adding .5 AMD to the inventory for an additional carrier battle group is a real world example of scaling AMD to fit demand. Another method is to disregard demand generated when the composition of the Sixth Fleet is different from that of the month being forecasted.

The second shortcoming is the perfunctory method used to compute variance of demand. In an inventory system, protection against variance in demand is obtained from safety stock. Richard J. Tersine defines safety stock as:

> . . .extra inventory kept on hand as a cushion against stockouts due to random perturbations of nature. They are needed to cover the demand during the replenishment lead time in case actual demand exceeds expected demand, or the lead time exceeds the expected lead time. [Ref 3: p. 210]

In this inventory system there are two distinct safety stocks, the one month safety level required by COMNAVSURFLANT (1 AMD) and the safety level to protect against variance in demand (.1 AMD). The COMNAVSURFLANT safety stock is a contingency stock required to protect against nondelivery of a scheduled monthly resupply. The .1 AMD safety stock protects against those times when actual demand exceeds expected demand. The use of .1 AMD as the computation for demand variance is an acknowledged guess, with no documented analysis. Safety levels, to protect against variance in demand, are usually a function of an item's standard deviation. James W. Prichard and Robert H. Eagle put it this way:

> . . .calculation of safety levels to meet specific management goals generally requires the estimation of demand, lead time, and the standard deviation of demand during lead time. [Ref 4: p. 162]

The most common effectiveness statistic for the 2.1 AMD methodology is the proportion of satisfied customer requirements. This measure, which ranges from 95% to 98%, is misleading because it counts partial issues as successful inventory actions [Ref 5]. This statistic does not measure how well an inventory supports the COMNAVSURFLANT goal of maintaining at least one AMD on hand at all times. A better operational measure of effectiveness would be one that evaluates the ability of an inventory, at the end of a cycle, to support an additional cycle without the receipt of a scheduled resupply. For the 2.1 AMD method the protection against preclusion of a scheduled resupply for the upcoming cycle is the COMNAVSURFLANT required

thirty day safety level and the .1 AMD variance factor not used in the previous month. In other words, the current methodology will meet the COMNAVSURFLANT goal and satisfy all customer requirements, for all items over two months, as long as demand does not exceed expected demand by ten percent.

C. MODIFIED AVERAGE MONTHLY DEMAND METHOD

In an effort to improve and standardize the process, the Commander Service Force Sixth Fleet (COMSERVFORSIXTHFLT) tasked USS Concord (AFS-5) with modifying the 2.1 AMD method by relating the number of sailors in theater to historical demand [Ref. 6]. This *modified AMD* method requires the computation of a quantity used per sailor per month and changes AMD from a generic measure to a normalized value which can be used to forecast demand based on the projected number of sailors to be supported. The computations are accomplished by first averaging the AMD per sailor rates over a suitable number of months. An average quantity used per man is then multiplied by the number of sailors projected to be supported in the forecast month. The general mathematical formulation for average demand per sailor is:

$$\overline{AMD_i} = \frac{\sum_{t=1}^{n}(D_{i,t} \div M_t)}{n} \qquad \text{for each i, where,} \qquad \{2\}$$

i	Item (i= 1,...., m) where m is the total number of items
t	Month (t= 1,...., n) where n is the current month
n	Number of months of historical demand in baseline
$D_{i,t}$	Monthly demand for item i in month t
M_t	Number of sailors supported for month t
$\overline{AMD_i}$	Average monthly demand per sailor for item i

The stocking objective for the Modified AMD Model is:

$$\text{Stocking Objective} = \sum_{i=1}^{m}(M_{n+1} \times \overline{AMD_i}) + (M_{n+2} \times \overline{AMD_i}) \qquad \{3\}$$

The normalizing of demand to measure monthly demand per sailor fixes the first shortcoming of the AMD method. It automatically adjusts demand data collected in months that significantly differ in the number of ships supported. The method does not

provide for safety stock to protect against variance in demand. Using this method allows the inventory manager to concentrate on demand that is a function of the number of sailors supported, a value that can be forecasted from deployment schedules.

This thesis focuses on improving the safety stock computations for variance in demand, the second shortcoming of the 2.1 AMD method. Historical data is used to analyze demand patterns and develop alternative models. The performance of the alternative models is then compared to the 2.1 AMD and Modified AMD Models. Emphasis is placed on developing an alternative model that satisfies all customer demand and maintains COMNAVSURFLANT's one AMD on hand at all times.

III. APPROACH

A. DATA BASE

The data to develop a forecasting model was obtained from actual Sixth Fleet demand generated from June 1986 to March 1988. Twenty-two months of data was extracted from USS Concord's SUADPS Master Record File (MRF). The data base contains item identification (National Stock Number and nomenclature), and, by month, the number of issues and total quantity demanded. A second data set of Sixth Fleet demand generated from April 1988 to September 1988 was obtained from USS Sylvania (AFS-2) and is used to compare forecasting models. This second data set was maintained on LOTUS 123 spreadsheet software. The demand data in the LOTUS 123 data base actually extends back to October 1987 with monthly demand recorded separately from, yet concurrently with, SUADPs demand data.[3]

The MRF demand record file, for each Atlantic Fleet AFS, reflects monthly demand for the previous 24 months. Each month, the on station AFS mails to all other AFSs demand tapes reflecting all issues made that month by CLF ships to customer ships deployed to the Sixth Fleet. MRF demand records are updated by each AFS by combining the Sixth Fleet demand with any demand generated through issues to own ship's use or to customers during local (Second Fleet) operations. This additional demand, different for each AFS, is usually small compared to Sixth Fleet generated demand. Because of this basic uniformity in demand records, the Concord data is assumed to be representative of data available from other AFSs.

Due to the many different units of issue for provisions, HULL, and QCOG, all units of issue are converted to cubic feet, ensuring consistency of unit dimension. Demand data is first normalized based on the Modified AMD Model. The number of sailors supported for each month of data is determined using the ships listed on Monthly Effectiveness Reports (generated by the on station AFS) and the approximate crew sizes listed in Appendix A, Table 7. Then the Modified AMD Model, Equation 2, is used to compute the quantity used per sailor per month. To preserve significant digits the actual computation, used throughout the thesis, is scaled to compute the quantity used per

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[3] The demand data used in this thesis is available on request from the author. Data is in SUADPS MRF record and LOTUS 123 format and will be provided on a standard 5.5 inch diskette.

1000 sailors per month. Appendix A, Table 8, provides the approximate number of sailors supported for each of the 28 months of demand data.[4]

B. DATA VALIDATION

Discrepancies in the SUADPS data base were found when comparing demand data to other records that maintain the same historical demand. This limited all initial analysis and model development to QCOG items, because QCOG is the only commodity that, when verified against LOTUS demand, appears on average to be accurate. The SUADPS demand records for dry provisions were incomplete. Many monthly demand entries for dry provisions were completely missing, a fact that limited data validation for provisions to freeze provisions only. SUADPS demand records for freeze provisions are evaluated by reconstructing Sixth Fleet inventory levels from callout messages, NSC Norfolk issue records, and SUADPS demand records. After a period of time (nine months), the reconstructed inventory level is compared to a known inventory level. Due to insufficient documentation the same procedure could not be duplicated for HULL and QCOG items. Validation of HULL and QCOG demand data is accomplished by directly comparing SUADPS records to LOTUS records.

The comparison begins with the January 1988 LOGREP cycle. Concord deployment records are used to determine January 1 beginning inventory. Additions (receipts) to each item's inventory are applied based on issue records provided by NSC Norfolk. Provisions enter the Mediterranean either through resupplies generated by an on station AFS or by being brought over by a deploying CLF ship supporting a carrier or battleship battle group. In either case, all provisions are initially issued by NSC Norfolk. The issues to be subtracted from the inventory are taken from both the SUADPS and LOTUS data bases, generating two comparisons. Finally, the ending inventories are obtained from a September 2, 1988 USS San Diego (AFS-6) callout message. It stated that the October beginning inventory goal was 2.1 AMD and provided the AMD values. Appendix B, Tables 9 and 10, recap the monthly inventory actions for both data bases (SUADPS demand and LOTUS demand) from January 1, 1988 to October 1, 1988 for frozen ground beef (Q31), frozen beef tenderloin (Q40), and frozen mustard greens (S92).

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[4] The Monthly Effectiveness Report for June, 1987 was not available. This prevented the author from computing quantity used per sailor and eliminated the June, 1987 demand from subsequent data analysis.

Table 2 highlights the results of the nine month comparison. Analyzing these results requires that the following assumptions be made concerning these three provision items:

- Their actual inventories on January 1, 1988 and October 1, 1988 were equal to the projections made by the on station AFS.
- No provisions were lost through survey.
- No provisions were returned (unsold) to NSC Norfolk during this time period (a COMNAVSURFLANT Notice 4423 goal).
- NSC Norfolk issue records are correct.
- The USS Milwaukee made no issues of the three items during her transit to the Mediterranean.

A reconstructed inventory that is greater than the actual inventory means either that inventory was lost or that issues were made and not recorded. The nine month comparison shows that both the SUADPS and LOTUS reconstructed inventories, for all three freeze provision items, are greater than actual inventories. The loss of material or missing issues with SUADPS demand data is significant. The loss of ground beef (Q31) alone was over 150 measurement tons (MT). For all three items, the reconstructed inventory is close to three times the actual inventory. Although the same comparison, using LOTUS demand, provides a large improvement relative to the SUADPS results however, there is still an understatement of issues.

Table 2. TEN MONTH INVENTORY REVIEW

Data Base	EVENT	Provision Item Number		
		Q31	Q40	S92
Actual	10/1/88 Projected Inventory (lbs)	86390	12382	3894
SUADPS	Reconstructed Inventory (lb)	341346	50274	13467
	Inventory Loss (lb)	254956	37892	9573
	Inventory Loss (MT)	153.0	17.0	10.9
LOTUS	Reconstructed Inventory (lb)	133244	14654	4782
	Inventory Loss (lb)	46854	2272	888
	Inventory Loss (MT)	28.1	1.0	1.0

Direct comparison of the two data bases (SUADPS and LOTUS) provides a method to further analyze their accuracy. Although maintained in tandem, SUADPS and

LOTUS have different uses. The SUADPS files are updated with demand through the UNREP software and are primarily used to maintain own ship's inventory. The LOTUS files are used by the on station AFS to manage Sixth Fleet inventories and are considered the more accurate record.

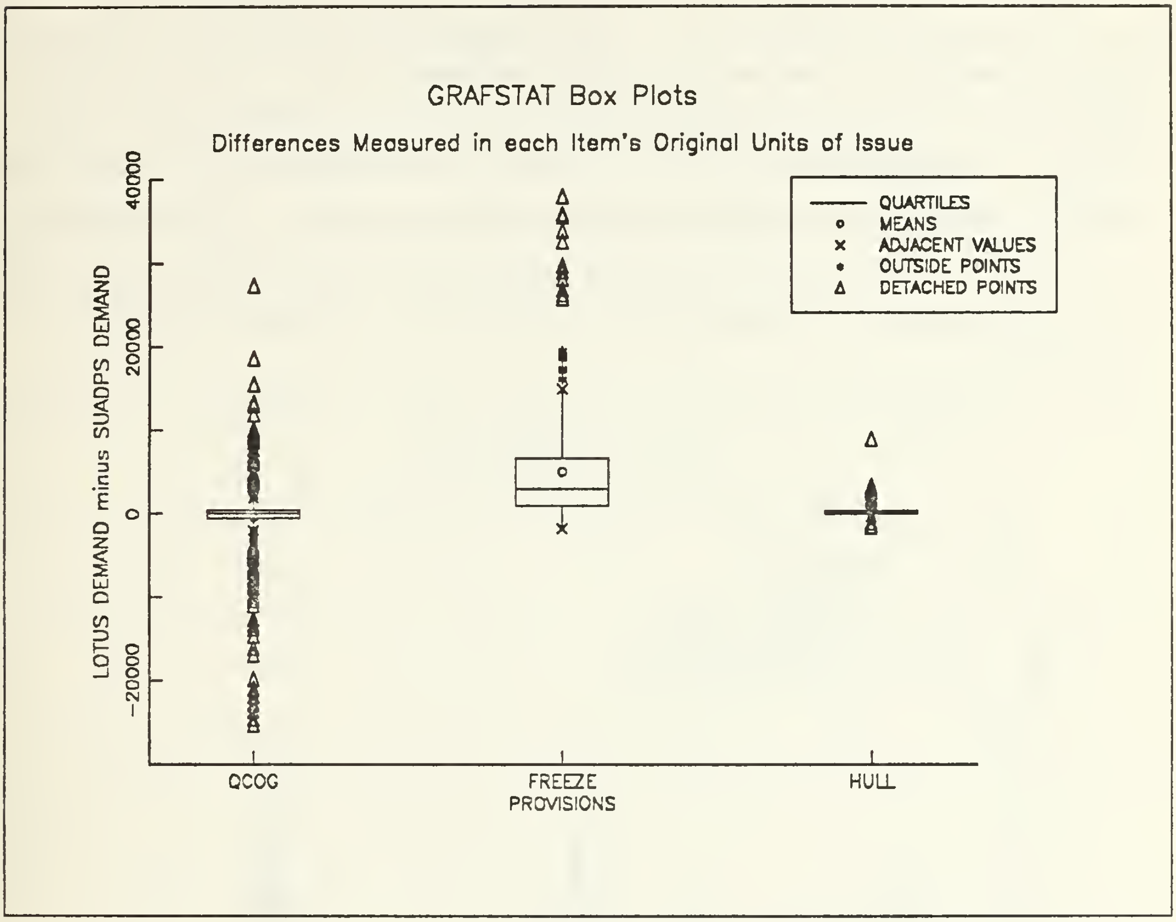

Figure 1. Box Plot Comparison of LOTUS and SUADPS Demand Records

Monthly issue quantities for the two data bases are compared for freeze provisions, HULL, and QCOG items over a six month period, October 1987 to March 1988. For the comparison, SUADPS demand is subtracted from the LOTUS demand. Figure 1 is a GRAFSTAT produced Box Plot of the differences between LOTUS and SUADPS demand measured in each item's standard unit of issue. The *box* portion of the plot contains the middle 50% of the data points. The line across the center of the plot (clearly visible only for freeze provisions) marks the median. The vertical width of the box is called the interquartile distance (Q) and is the basis for identifying points outside the box. Adjacent points (x) are 1.5 times Q away from the median, outside points (*)

are 1.5 to 3.0 times Q away from the median, and detached points (Δ) are more than 3.0 times Q away from the median. Observations below zero mean that the demand recorded in SUADPS exceeded the demand recorded in LOTUS. Observations above zero are analogous.

The median being above zero and the majority of points lying above the box for freeze provisions is in agreement with what was found in the ten month inventory review. The QCOG data has a relatively even spread of observations around zero, although the distance of outliers above and below zero indicates that for some months there is considerable disagreement between the two data bases. HULL items seem to provide the best agreement between the two data bases. However, HULL items are high volume items per unit of issue and are not requested in the same quantities as provisions and QCOG.

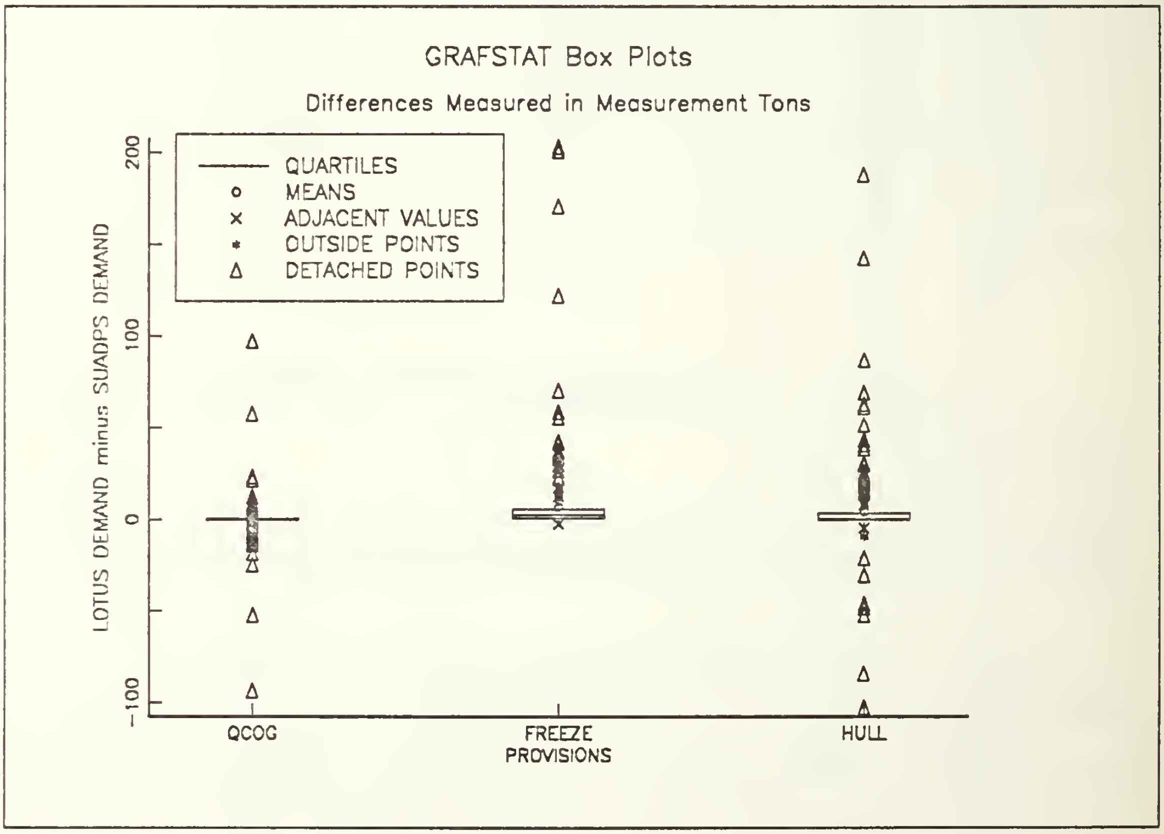

Figure 2. Box Plot Comparison of LOTUS and SUADPS Demand Records

Figure 2 is another Box Plot of the difference between LOTUS demand and SUADPS demand, this time measured in measurement tons. With this plot it becomes

clearer that the initial agreement for HULL items between the two data bases was achieved because of the relatively small numbers demanded. In Figure 2 both freeze provisions and HULL items have greater demand quantities recorded in LOTUS than SUADPS for the same months of demand. Specifically, Figures 1 and 2 show that the SUADPS data base is missing demand that has been recorded in LOTUS. The same conclusion can not be drawn for QCOG items. Both Figures 1 and 2 show that when there is a difference in a demand observation for a QCOG item that the greater demand does not tend to be in one or the other of the data bases. This even split in differences of QCOG demand observations indicates that while the two data bases do not always agree, neither data base can be considered more accurate.

A possible explanation for the discrepancies in the SUADPS records is the off line management of inventory, facilitated by micro computers. Micro computers offer flexibility not available from the AFS's Automated Data Processing (ADP) computers and are used to supplement the archaic Underway Replenishment (UNREP) software. Off-the-shelf spread sheet software is used to track inventory levels and compute callouts. This procedure requires maintaining two sets of demand records; one for the micro computer software and one for UNREP. At the end of each cycle, the UNREP data base is used to update SUADPS records. During this process, own ship's issues are automatically segregated from the issues made by other CLF ships. This is done to generate financial returns that reflect only own ship's issues. These financial returns, closely monitored by COMNAVSURFLANT, motivate accurate accounting of own ship's issues. Accurate recording of total Sixth Fleet demand is not monitored and is required only to perform Sixth Fleet inventory manager duties, i.e. forecasting of future inventory levels. Therefore, with total Sixth Fleet demand already recorded on a micro computer data base that is used to manage inventory levels, there is little incentive to record demand other than own ship's issues a second time into UNREP or SUADPS.

If all issues made by CLF ships (provisions and HULL) are not being recorded into SUADPS, then both provision and HULL demand data is inaccurate. Two factors improve the likelihood of accurate SUADPS demand records for QCOG items. First, all QCOG issues are made by the on station AFS. Second, for the AFS to have accurate financial records, all QCOG issues must be recorded into SUADPS either through the UNREP software or by some other means. For this thesis, SUADPS QCOG demand records are assumed accurate and all data analysis and initial model development is limited to the 130 QCOG items listed in Appendix C.

C. DATA ANALYSIS

To facilitate data analysis the author used A Programming Language (APL) to manipulate and to ready demand data for two statistical analysis packages, GRAFSTAT and STATGRAPHICS. The univariate characteristics for the number of monthly issues and quantity issued are reviewed using STATGRAPHICS *codebook* procedures. This provides a range (minimum and maximum), mean, variance and skewness for both data elements. Next, histograms are used to summarize the shape of the distribution density for quantity demanded per man per month. A picture of the resulting density, although relatively nontechnical, provides initial insight into possible distribution candidates to fit the empirical data.

Distributions are tested using GRAFSTAT quantile-quantile plots. Because increasing the number of observations provides better results all available data, except for the six months set aside for model comparison, is used for data analysis. Parameters for the theoretical distributions are estimated from results obtained during univariate analysis. Finding a distribution that *fits* the historical demand would explain the mechanisms driving the data and would provide a means to compute the probability of future demand exceeding a given level of inventory. Distribution candidates are initially chosen based on the mode and skewness characteristics. Only QCOG items experiencing more than ten months of demand are tested.

In addition to the quantile-quantile plots, GRAFSTAT performs a goodness of fit test using the Kolmogorov-Smirnov test statistic. The null hypothesis, that the empirical demand data has a particular theoretical distribution, is tested at a 5% significance level. In terms of acceptance, a 5% significance level means that the maximum probability of ***not*** accepting a true null hypothesis is 5%.

IV. ANALYSIS RESULTS

A. UNIVARIATE ANALYSIS

Results obtained from STATGRAPHICS *codebook* for the two categories of data, monthly issues, and monthly quantity issued per one thousand sailors, are provided in Appendix D. Because the Monthly Effectiveness Report for June 1987 was not available, demand data for that month is not used in computing univariate characteristics. One consistent result was positive skewness, found for all items in both categories.

Data analysis continued using GRAFSTAT to construct histograms in order to determine the general shape of the density for the distribution of demand. GRAFSTAT produces a general, equal bin size histogram. The number of bins constructed with the histogram function is approximately $1 + \log_2(\#data\ points)$. For 21 data points (21 months of demand) seven bins will normally be produced. Most of the histograms displayed a distribution that is unimodal and positively skewed. Figure 3 is an example of the histograms obtained using these procedures.

Figure 3. Sample Histogram Produced with GRAFSTAT

Combining probability theory with the results of the univariate calculations and histogram constructions allows the computation of an upper bound for the probability of a stock out. A stockout occurs when demand exceeds inventory. The computation of an upper bound for the probability of a stockout provides an opportunity to analyze the theoretical efficiency of the .1 AMD factor currently used to protect against variances in monthly demand. In standard probability notation [Ref 7: p. 157]:

$$P(X \geq \mu + b\sigma) \leq \frac{1}{1 + b^2} \qquad \{4\}$$

X	The unknown monthly demand for which the probability is to be computed (demand from a nonnegative distribution).
μ	Mean demand.
σ	Standard deviation of demand.
b	Multiple of standard deviations.

Equation 4 allows the computation of the probability of demand in some future month exceeding the mean plus a multiple of the standard deviation. To meet the expected demand for the next LOGREP cycle, the current method of computing inventory levels adds to the mean (1 AMD) a multiple of the mean (.1 AMD) vice a multiple of the standard deviation. Equation 4 is applied to the 2.1 AMD methodology by equating .1 AMD to b times σ . For the 2.1 AMD Model if demand exceeds 1.1 AMD then the COMNAVSURFLANT requirement of maintaining at least one AMD on hand at all times is not achieved. Table 3 evaluates the upper bound for the probability of demand exceeding 1.1 AMD in some future month for four popular QCOG items.

The table shows that demand for these four items will, with almost certainty, exceed 1.1 AMD in some future month. Equation 4 can be used to improve inventory effectiveness. By setting b equal to two in Equation 4, one can compute the upper bound that the probability of demand in some future month will exceed the mean (1 AMD) plus <u>two</u> standard deviations. This probability is 20% versus the 94.9% to 99.3% originally achieved with the 2.1 AMD Model. These probability estimates of **not** meeting COMNAVSURFLANT's one AMD goal are conservative and can be improved with

Table 3. UPPER BOUND ON P(MONTHLY DEMAND) ≥ 1.1 AMD

All Units in Cubic Feet per 1000 Sailors Supported				
Item	Mean (1 AMD)	Standard Deviation (σ)	b given $b\sigma = .1AMD$	$\frac{1}{1+b^2}$
Snickers	6.13	2.64	0.232	0.949
Marlboro	19.77	8.87	0.223	0.953
Audio Cassettes	3.18	1.94	0.164	0.974
Aim Toothpaste	1.13	1.37	0.082	0.993

results from the univariate analysis. Since the histograms indicate that the unknown distribution of monthly demand for QCOG is unimodal, the 20% upper bound of not meeting the COMNAVSURFLANT goal using two standard deviations for protection against variance in demand is overstated. The Camp-Meidel extension to Tchebychev's inequality states:

> If the distribution of X is unimodal, the probability that X should deviate from its mean more than b times ($b \geq 1$) is equal to or less than 1/(2.25 b^2). [Ref 8: p. 104]

In standard probability notation:

$$P(X < \mu - b\sigma \text{ or } X > \mu + b\sigma) \leq \frac{1}{2.25 \times b^2} \qquad \{5\}$$

Again, with inventory levels set at one AMD plus two standard deviations ($b = 2$), Equation 5 sets the probability of not meeting the COMNAVSURFLANT goal to be no greater than 11%. Thus with the initial information provided by the construction of histograms, the upper bound for the probability of not meeting the COMNAVSURFLANT goal is reduced to 11%, well below the 20% first computed. The computation of the probability of demand exceeding an inventory quantity can be further refined if the underlying distribution of demand is known.

B. DISTRIBUTION FIT

The process of fitting demand data to distributions improves as the number of data points increases. Only QCOG items experiencing demand in at least ten of the 22 months of data were selected for the distribution fitting process. Of the 130 QCOG items, 120 met this criteria. The univariate analysis and histogram construction revealed

the following initial characteristics for the underlying demand distribution for those 120 QCOG items:

1. **Continuous Distribution** - Monthly demand, after being normalized for sailors supported and having units of issue changed to measurement tons, no longer has finite and discrete values. Demand, now expressed in terms of volume, can be any value over a continuous range.
2. **Positive Distribution** - All values of demand are either zero or some positive value.
3. **Positive Skewness** - During univariate analysis, all items had a positive third sample moment.
4. **Unimodal** - During histogram construction, most items had a single peak or mode.

A positively skewed demand distribution generally has a greater probability than a symmetric or negatively skewed distribution of experiencing demand in the right tail of the distribution. Demands in the right tail of the distribution can be thought of as upward spikes in demand.

Two distributions, the lognormal and gamma distributions, best meet these initial prerequisites. GRAFSTAT quantile-quantile plots are used to check the fit of the data to these two theoretical distributions. Figure 4 is an example of GRAFSTAT-generated quantile-quantile plots for fitting the lognormal and gamma distributions to the demand data for Zest soap. When the theoretical distribution is a close approximation of the empirical distribution, the points on the quantile-quantile plot will fall near the solid diagonal line. Figure 4 also provides 95% confidence bounds for the plotted points. When the theoretical distribution does not pass the confidence test, the bounds will intersect the solid diagonal line. Appendix E provides the Kolmogorov-Smirnov goodness of fit test statistic for each item having, more than ten demand observations.

Both distributions fit the data with very high acceptance levels. No items are rejected at a 5% level of significance with the lognormal distribution and two items are rejected with the gamma distribution. Which distribution provides the best fit? The two distributions are split 58 in favor of the lognormal distribution and 62 in favor of the gamma distribution. Overall the gamma distribution provides the better fit for confectionery and tobacco products while the lognormal provides the better fit for toiletry and clothing items. Since both distributions provide *good* fits, the much easier to handle lognormal distribution is selected as the underlying distribution of demand for model development.

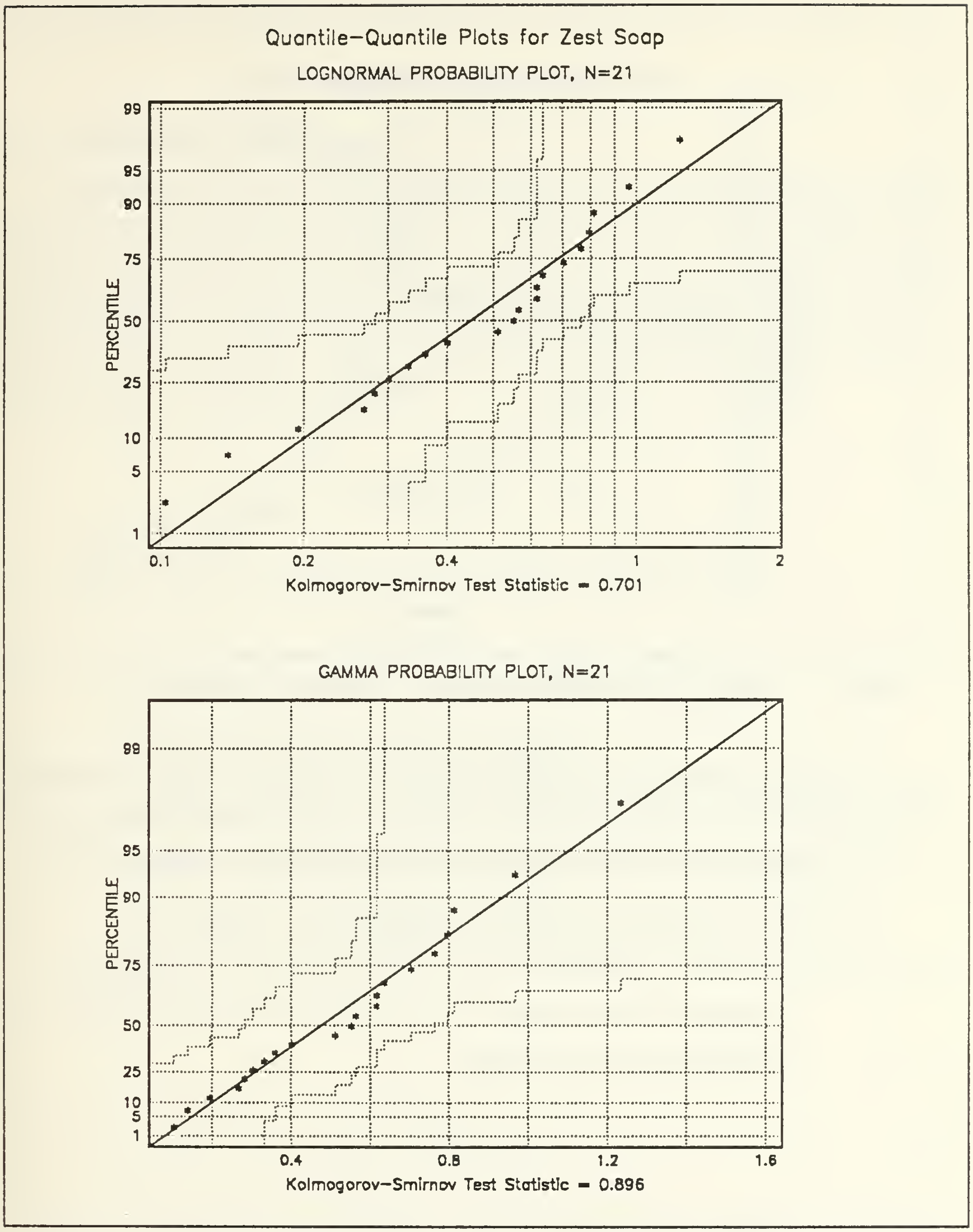

Figure 4. Quantile-Quantile Plots for Lognormal and Gamma Distribution

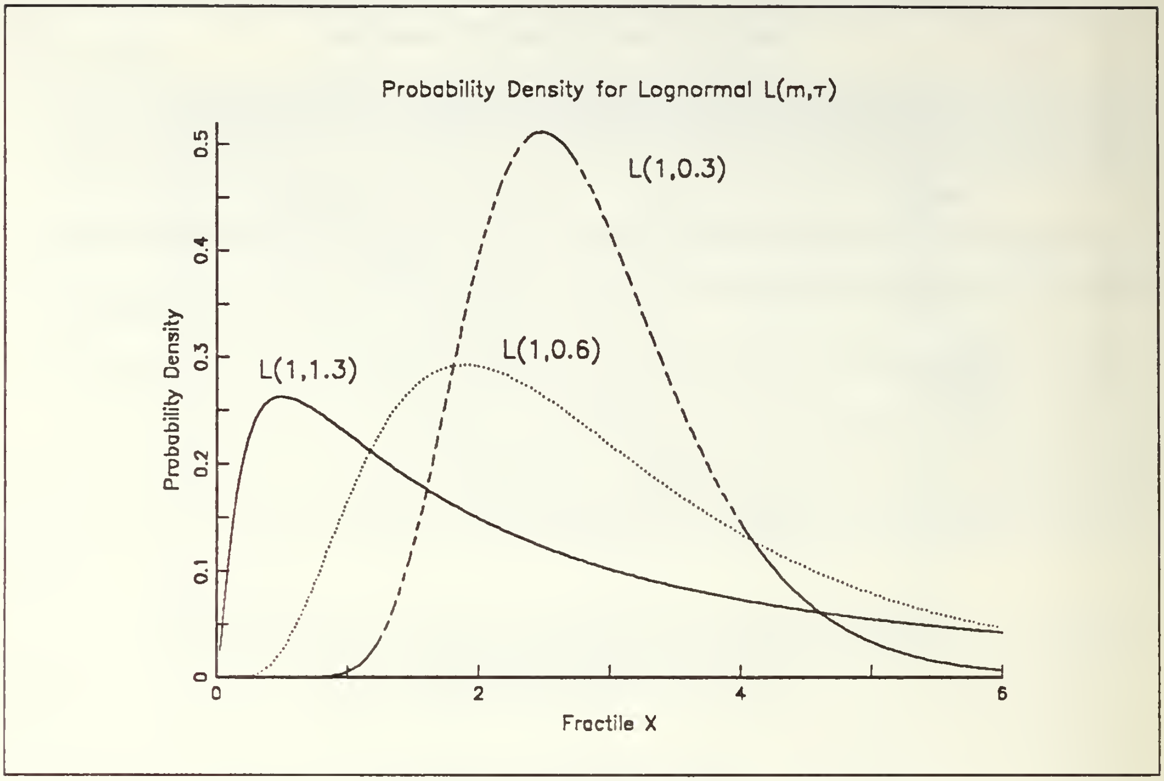

Figure 5. **Shapes of the Density Function for Lognormal Distribution**

What does the lognormal distribution look like? Figure 5 provides examples of the various unimodal and positively skewed shapes of the lognormal density function. The probability density function for the lognormal distribution $L(m, \sigma)$ has the form:

$$f(x) = \frac{1}{x\sigma(2\pi)^{\frac{1}{2}}} \exp\left\{\frac{-\left[\ln xe^{-\mu}\right]^2}{2\sigma^2}\right\} \quad \text{where,} \qquad \{6\}$$

μ	Lognormal scale parameter
σ	Lognormal shape parameter

V. MODEL DEVELOPMENT

A. LOGNORMAL MODEL

Computations for the Lognormal Model are based on the lognormal distribution's relationship with the normal distribution. The density function for the lognormal distribution, when plotted on a logarithmic scale, is normal.[5] That is, taking the natural log of the demand data transforms the monthly demand values into a set of normally distributed random variables. This transformation provides a method to estimate the lognormal scale and shape parameters:

$$\hat{\mu} = \frac{1}{n} \times \sum_{i=1}^{n} \ln x_i \qquad \text{and,} \tag{7}$$

$$\hat{\sigma}^2 = \left(\frac{1}{n-1}\right) \times \sum_{i=1}^{n} (\ln x_i - \hat{\mu})^2 \qquad \text{where,} \tag{8}$$

n	Number of months of historical demand
x_i	Monthly demand (normalized for number of sailors supported), where i ranges from 1 to n
$\hat{\mu}$	Sample mean of the log of the data, lognormal scale parameter
$\hat{\sigma}^2$	Sample variance of the log of the data, lognormal shape parameter

For the lognormal distribution, the values for the mean (AMD) and sample variance are computed using the following equations:

$$\bar{\mu} = e^{(\hat{\mu} + \frac{\hat{\sigma}^2}{2})} \qquad \text{and,} \tag{9}$$

$$\bar{\sigma}^2 = e^{(2\hat{\mu} + \hat{\sigma}^2)}(e^{\hat{\sigma}^2} - 1) \tag{10}$$

Since a natural log transformation of the data yields a distribution that is approximately normally distributed, $N(\hat{\mu}, \hat{\sigma}^2)$, inventory levels can be computed in terms of the

---

[5] The use of the term log, unless otherwise stated, refers to natural logarithms.

sample log mean ($\hat{\mu}$) and multiples (b) of sample log standard deviation ($\hat{\sigma}$). This simplifies the process of equating inventory levels to a level of support. In this context, a level of support is:

$$\text{Level of Support} = 1 - \text{P(stockout)} \qquad \{11\}$$

As previously stated, the probability of a stockout is the probability that demand will exceed inventory. Therefore, a level of support for an item is the probability that demand in some future month will not surpass the item's inventory. Since demand is normally distributed (after the log transformation) a level of support for the natural log of some unknown future monthly demand (X) can be stated in terms of inventory levels that are computed with an item's sample log mean ($\hat{\mu}$) and multiple (b) of the sample log standard deviation ($\hat{\sigma}$). A level of support is expressed with the following notation:

$$\text{Level of Support} = \text{P}(X \leq \hat{\mu} + b(\hat{\sigma})) \qquad \{12\}$$

Using the standard normal transformation, the on station AFS can compute the value of b from standard normal cumulative density tables. The level of support is equal to the area under the standard normal curve from $-\infty$ to b In most tables this area is called $F_Z(b)$ and each $F_Z(b)$ (or level of support) yields a specific value of b . Table 4 provides the number of standard deviations, added to the mean, required to achieve various levels of support.

Table 4. LEVELS OF SUPPORT FOR LOGNORMAL MODEL

Level of Support	50%	75%	90%	95%
# Standard Deviations	0	.68	1.28	1.65

An item's actual inventory level or stocking objective using the lognormal distribution is composed of two components. One component ($e^{\hat{\mu} - b\hat{\sigma}}$) both meets the expected demand for the upcoming LOGREP cycle and provides protection against variance in demand. The other component ($\overline{\mu}$) meets COMNAVSURFLANT's one AMD goal. All historical demand for the Lognormal Model is normalized for the number of sailors supported. For a month that has a resupply scheduled after completion of the LOGREP

cycle, the stocking objective for the Lognormal Model is computed with the following equation:

$$\text{Stocking Objective} = (M_{n+2} \times \overline{AMD_i}) + (M_{n+1} \times e^{(\hat{\mu}_i + b(\hat{\sigma}_i))}) \qquad \text{where,} \qquad \{13\}$$

i	Item (i = 1,..., m) where m is the total number of items
n	Number of months of historical demand in baseline
b	Multiple of standard deviations associated with a desired level of support
M_t	Number of sailors supported for month t
$\overline{AMD_i}$	Average monthly demand per sailor for item i

B. IN SEARCH OF A SIMPLER RULE: POINT ESTIMATE MODEL

The current method of setting inventory levels for provisions, HULL, and QCOG, in terms of multiples of the mean (AMD), is understood and widely accepted. Initial analysis of the 2.1 AMD Model with the upper probability bounds for stockouts supports the premise that the on station AFS can achieve better results using a combination of the mean and standard deviation. With the underlying distribution assumed to be lognormal the process of setting inventory levels requires the computation of natural logarithms and exponentials. While this process is mathematically sound, it may not be widely understood (or accepted) by inventory mangers. Ideally a *simpler rule* would be a model that expresses the inventory calculations in terms already understood, for example, AMD.

Prichard and Eagle suggest developing a direct relationship between the mean and standard deviation for a complete inventory of items as a simple technique for measuring dispersion [Ref 4: p. 163]. Simple linear regression is used to explore this relationship. Each item's sample standard deviation is assigned as a dependent variable (y axis) and each items sample mean is assigned as an independent variable (x axis).

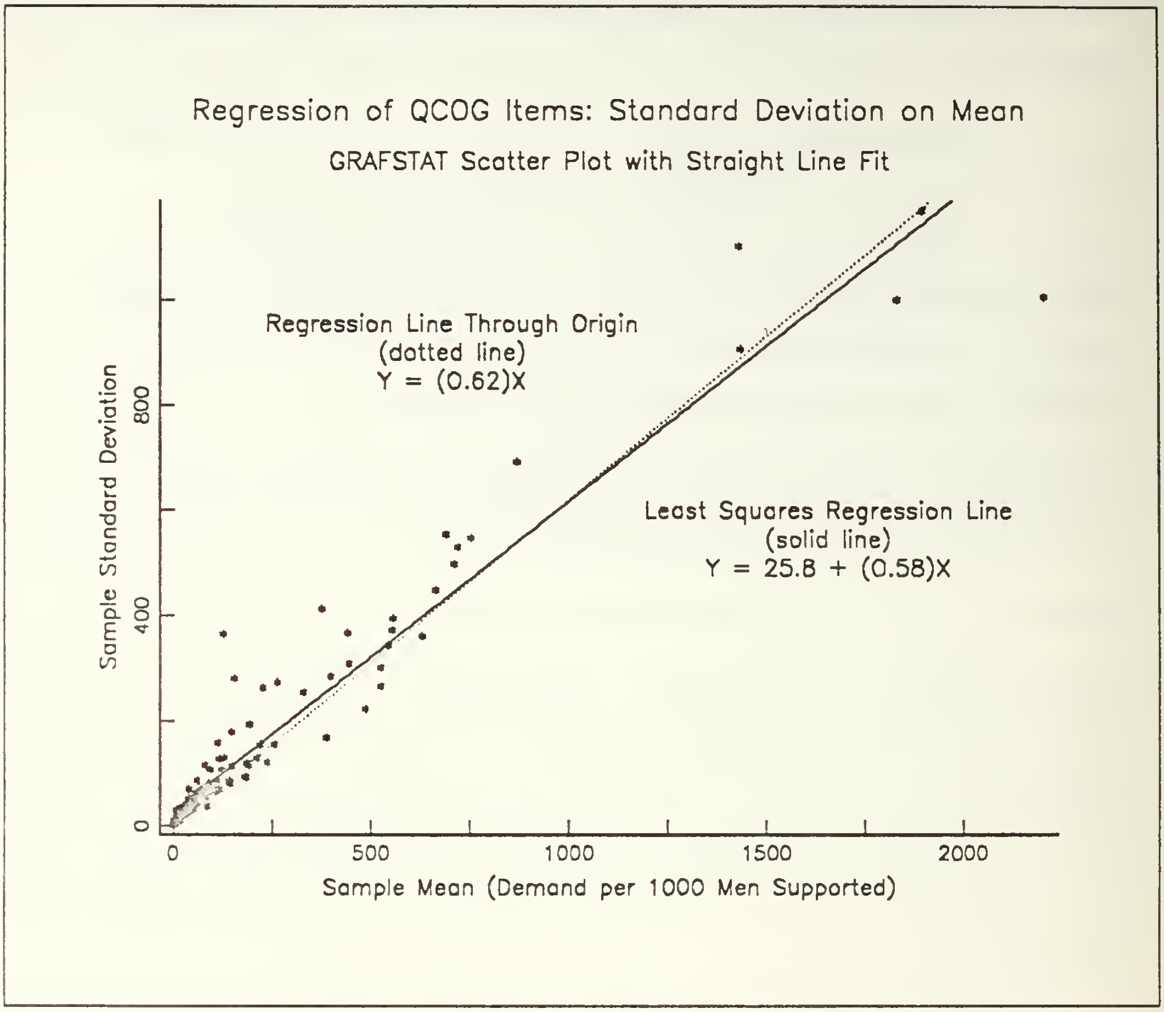

Figure 6. Regression of Standard Deviation on Mean for QCOG Items

GRAFSTAT scatterplot and curve fitting plot screens are used to perform the regression illustrated in Figure 6. Two lines are plotted. The solid line is the least square regression line and the dashed line is a least squares regression line through the origin. Since the least squares regression y-intercept is close to the origin, relative to the plots scale, most of the significance in the relationship is contained in the slope of the line. Each line's slope provides the multiple of x's (sample mean) that constitute a y (sample standard deviation).

From this linear relationship and the lognormal distribution, the computations for inventory levels can be stated in terms of AMD. The method is called the Point Estimate Model and is derived by computing a point estimate for $\hat{\sigma}$ from the slope of the

regression line and mathematically manipulating the stocking objective for the Lognormal Model (Equation 13). The mathematical derivation of the Point Estimate Model is provided in Appendix F.

For QCOG items the final form of the stocking objective for the Point Estimate Model, at a 95% level of support, is:

$$\text{Stocking Objective} = (M_{n+2} \times \overline{AMD_i}) + (M_{n+1} \times 2.1 \times \overline{AMD_i}) \qquad \text{where,} \qquad \{14\}$$

i	Item (i = 1,..., m) where m is the total number of items
n	Number of months of historical demand in baseline
M_t	Number of sailors supported for month t
$\overline{AMD_i}$	Average monthly demand per sailor for item i in month t

Equation 14 provides the *simpler rule*. The Point Estimate Model's stocking objective for QCOG in a month when a resupply will be received at the end of the month is 3.1 AMD. Even though its stocking objective is stated in terms of AMD, the Point Estimate Model bases its protection against variance in demand on standard deviations (point estimate). The Point Estimate Model, like the Lognormal Model, sets inventory levels based on a level of support. As with the Lognormal Model a level of support determines the multiple (b) of standard deviations, added to the mean, required to provide that support. In Equation 14 the level of support was 95%, requiring a b value equal to 1.65. (See Table 4.)

VI. MODEL COMPARISON

A. HYPOTHESIS

The objectives for a Sixth Fleet AFS resupply model are two-fold. First, the model must forecast inventory levels that will provide customers with 100% of what they request. Second, the model is to set inventory levels that will maintain the COMNAVSURFLANT directed safety levels, equal to one AMD on hand at all times. The two models that evolved from analyzing historical demand set protection levels based on the sample variance (standard deviation). The hypothesis is that these two new models should outperform the two models that base their protection levels on the sample mean.

Six LOGREP cycles are simulated to compare model performance and to test the hypothesis that a model based on sample variance will out perform the model currently used. The performances of the following six variations of the four resupply models are compared:

Model A AMD Method: AMD computed from the last six months demand.

Model B AMD Method: AMD computed from the last twelve months demand.

Model C Modified AMD: AMD computed from the last six months demand normalized for the number of sailors supported.

Model D Modified AMD: AMD computed from the last twelve months demand normalized for the number of sailors supported.

Model E Point Estimate Model: Inventory levels based on last twelve months demand normalized for the number of sailors supported.

Model F Lognormal Model: Inventory levels based on last twelve months demand normalized for the number of sailors supported.

B. MEASURES OF EFFECTIVENESS

The modeler's goal is to reproduce the real world. The tool used in determining how close a modeler comes to the real world is the Measure of Effectiveness (MOE). Selecting unbiased and effective MOEs is of utmost importance when comparing the performance of alternative models. MOEs must be related to the objective of the model and provide quantitative and measurable results. The following three measures of effectiveness are used to compare the performance of the models listed above.

1. Monthly Effectiveness

Currently, this is one of the indicators used to measure the performance of the on station AFS's inventory management. The on station AFS reports a ratio of issues to customer requisitions. Whether the quantity provided is as much as the quantity demanded is not considered. This allows partial issues to be counted as successful inventory actions.

Not knowing customer requisition quantities and delivery order precludes the usual calculations for monthly effectiveness. All that is available from the LOTUS data base is the total quantity demanded. Therefore, monthly effectiveness is changed to measure a model's ability to satisfy all demand with all of its theoretical "beginning of the month" inventory. Monthly effectiveness is computed as the number of items that meet all demand divided by the total number of different items ordered. This way, partial issues are not counted as successful inventory actions. Beginning inventories are set to meet expected customer demand for one LOGREP cycle and COMNAVSURFLANT's one AMD goal. For each model, this means a component for expected demand, a component for a one month safety level, and a component for variance in demand. As an example, for the 2.1 AMD Model, this MOE measures the percent time that all demand is satisfied with all the 2.1 AMD beginning inventory. The monthly effectiveness MOE is calculated using the following ratio:

$$\text{Monthly Effectiveness} = \frac{\#\ \text{Items Meeting Demand}}{\#\ \text{Different Items Requested}} \qquad \{15\}$$

2. Safety Stock Effectiveness

COMNAVSURFLANT Notice 4423 states, "at least one month's SIXTHFLT AMD will always be on hand on board CLF ships."[6] No matter what inventory levels a model generates, the goal is for all items to have one AMD of inventory remaining after all customers have received LOGREP services. Tersine calls this one AMD of inventory *safety stock*. The safety stock effectiveness MOE provides a measure of each model's ability to achieve COMNAVSURFLANT's minimum inventory levels. This is a theoretical evaluation since the COMNAVSURFLANT one AMD is a safety level and a resupply would be received prior to commencement of the next LOGREP cycle.

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[6] This goal always is secondary to the goal of providing customers 100% of what they request. CLF ships do not withhold inventory in order to meet the COMNAVSURFLANT one AMD goal.

However, the measure is practical. One AMD is the protection against a scheduled resupply not arriving and would be expected to support the next LOGREP cycle.

Cycle effectiveness measures how the entire inventory performs at meeting customer demands. Safety stock effectiveness measures how the inventory designated to meet expected demand and to protect against variance in demand performs that task. Safety stock effectiveness is computed as the number of items at the end of a LOGREP cycle with at least a one AMD inventory level divided by the total number of different items ordered. As an example, for the 2.1 AMD Model this MOE measures the percentage of items for which demand does not exceed 1.1 AMD. The safety stock effectiveness MOE is calculated using the following ratio:

$$\text{Safety Stock Effectiveness} = \frac{\#\ \text{Items Maintaining One AMD}}{\#\ \text{Different Items Requested}} \qquad \{16\}$$

In other words, safety stock effectiveness is the percentage of items that experience demand less than the inventory levels generated to meet that demand. If either the Lognormal Model or the Point Estimate Model reproduce the real world, then the safety stock effectiveness for the model should equal its predetermined level of support. Recall that these two models compute inventory levels to meet customer demand (and provide protection against variance in demand) by adding multiples of the standard deviation to the mean. The standard deviation multiplier is determined from the level of support set by the inventory manager. (See Table 4.) A level of support is the probability that some future demand will be less than the inventory levels generated to meet that demand. Safety stock effectiveness measures what has actually happened. Therefore, when the level of support assigned to a model equals the safety stock effectiveness achieved by the model, the model has reproduced the real world.

3. Inventory Volume

This MOE provides a value to test the feasibility of the beginning inventory generated by each model. One of the AFS's inventory management responsibilities is to ensure inventories will *fit* within the available storage space. Each model's beginning inventory quantity is computed, in measurement tons, for a value can that be used by the inventory manager to determine if space is a constraining factor.

C. SIMULATION PROCEDURE

A second data set of six months (4/88-9/88) historical demand is used to simulate LOGREP demands from Sixth Fleet customers. This data was not used in the original data analysis and model development. The simulation uses the following assumptions:

- LOTUS demand data is accurate.
- Inventory levels are rounded up to full case quantities.
- The Sixth Fleet deployment schedule is known with certainty by the AFS before callouts are due to NSC Norfolk.
- The 2.1 AMD Model (models A and B) have an extra .5 AMD added to the expected demand component for August, a two carrier battle group month.
- The level of support (Equation 11) is 95% for the Point Estimate Model and Lognormal Model.

In order to track each models performance relative to the three MOEs, the simulation generates the following information:

Demand	Input values for each QCOG item taken from demand generated in the Sixth Fleet from April 1988 to September 1988.
Beginning Inventory	Computed monthly and set at the high limit each model would forecast knowing the number and type of ships to be supported.
Inventory Volume	Measurement ton total of beginning inventory.
Cycle Shorts	Monthly number of QCOG items where demand exceeded inventory.
Safety Shorts	Monthly number of QCOG items not meeting the one AMD ending inventory requirement.

D. SIMULATION RESULTS

Table 5 provides the MOE values achieved by each model. The most obvious result is that effectiveness improves with increased inventory levels. The question then becomes, why did the Point Estimate Model and Lognormal Model (Models E and F) generate larger beginning inventories. The simulation allowed the models to recompute inventories each month, without regard for the previous month's ending inventory. The Point Estimate Model and Lognormal Model (E and F) generate higher beginning inventories because their protection levels against spikes in demand are tied to historical variance in demand. The 2.1 AMD Model and Modified AMD Model (Models A, B, C, and D) base their protection against spikes in demand on .1 times an AMD.

The Point Estimate Model (E) does not perform at the expected 95% level of support (safety stock effectiveness) in meeting COMNAVSURFLANT's goal of one AMD

Table 5. RESUPPLY MODEL MOE RESULTS

Month	MOE	Model					
		A	B	C	D	E	F
4 88	Monthly Effectiveness	0.978	0.978	0.967	0.967	0.978	1.000
	Safety Stock Effectiveness	0.889	0.900	0.822	0.856	0.967	0.967
	Inventory Volume (MT)	185.0	171.3	150.7	147.7	217.3	256.3
5 88	Monthly Effectiveness	0.910	0.960	0.960	0.960	0.990	1.000
	Safety Stock Effectiveness	0.720	0.730	0.840	0.870	0.970	1.000
	Inventory Volume (MT)	162.6	163.1	217.2	208.1	307.4	369.1
6 88	Monthly Effectiveness	0.857	0.847	0.827	0.816	0.939	0.949
	Safety Stock Effectiveness	0.510	0.516	0.469	0.510	0.765	0.837
	Inventory Volume (MT)	153.3	153.4	139.5	140.8	207.1	241.9
7 88	Monthly Effectiveness	0.762	0.762	0.673	0.733	0.931	0.960
	Safety Stock Effectiveness	0.356	0.366	0.317	0.307	0.723	0.851
	Inventory Volume (MT)	163.8	157.7	148.0	146.2	215.3	250.7
8 88	Monthly Effectiveness	0.859	0.859	0.939	0.970	0.990	1.000
	Safety Stock Effectiveness	0.586	0.586	0.697	0.727	0.949	0.990
	Inventory Volume (MT)	218.5	212.6	299.4	303.0	408.8	519.4
9 88	Monthly Effectiveness	0.978	0.989	0.945	0.978	0.989	1.000
	Safety Stock Effectiveness	0.879	0.890	0.802	0.835	0.934	0.978
	Inventory Volume (MT)	185.6	188.9	140.9	157.2	207.4	262.4
Average Monthly Effectiveness		**.891**	**.899**	**.885**	**.904**	**.969**	**.985**
Average Safety Stock Effectiveness		**.657**	**.665**	**.658**	**.684**	**.885**	**.937**
Average Inventory Volume (MT)		**178**	**174**	**182**	**184**	**261**	**317**

on hand at all times. This happens because the Point Estimate Model (E) uses the same value for sample log standard deviation ($\hat{\sigma}$) for all items. Referring back to Figure 6, the point estimate of $\hat{\sigma}$ is an overestimate for points below the regression line and an underestimate for points above the regression line. During the simulation this point estimate of $\hat{\sigma}$ did not provide sufficient protection for those items above the regression line. The Lognormal Model (F) achieved an average safety stock effectiveness of 93.7%, close to its 95% expected level of support. The difference in safety stock effectiveness for the two models is centered around the sensitivity each QCOG item has to its sample standard deviation. The Point Estimate Model (E) estimates a single standard deviation for

all items while the Lognormal Model (F) computes a standard deviation for each QCOG item.

The simulation provides useful results for comparing the 2.1 AMD Models (A and B) and Modified AMD Models (C and D). Slightly better results were achieved with a twelve vice six month demand base. For months when the Sixth Fleet consisted of one carrier battle group (CVBG) and one Marine Amphibious Readiness Group (MARG) the 2.1 AMD Models (A and B) generated the larger inventory levels and provided better support. However, in May and August when Naval forces in the Sixth Fleet exceeded one CVBG and one MARG the Modified AMD Models (C and D) provided better support. The Modified AMD Models (C and D) are extremely sensitive to increases in force levels, so much so that their stocking levels in May and August significantly skew their averages. For the six month simulation, even though the 2.1 AMD Models (A and B) generated more beginning inventory four out of six times, the Modified AMD Models (C and D) generated higher average inventory levels. Neither the 2.1 AMD Models (A and B) or the Modified AMD Models (C and D) generate stocking objectives that are sufficient to meet customer demand or the COMNAVSURFLANT one AMD goal.

The on station AFS routinely increases inventory levels for months when the number of ships supported exceeds the norm. The basic question that must be answered by the inventory manager, when the force size increases, is ***how much*** must inventory levels be increased when not using normalized demand. For the month of August the 2.1 AMD Models (models A and B) have inventory levels increased, across the board, by .5 AMD. That was not enough. Using normalized demand saves inventory managers from having to answer the question ***how much*** because models that use normalized demand are automatically adjusted each month based on the number of sailors to be supported. In August the models using normalized demand convincingly out performed the models whose inventories were scaled up by .5 AMD.

E. PROVISIONS AND HULL REVISITED

The LOTUS files do not contain sufficient observations (monthly demands) to partition the data so that a model based on distribution fit could be developed and tested. However, additional analysis validated both the Lognormal Model and the Point Estimate Model as viable alternatives for determining inventory levels for provisions and HULL. A random sample of 50 provision and HULL items were fitted by lognormal distributions to verify that the lognormal distribution explained their demand patterns. All 50 items fit the lognormal distribution at a 95% level of confidence. Additionally,

linear regression of the standard deviation to an item's mean was performed to verify that the Point Estimate Model could be applied to provisions and HULL. The best linear fit was achieved when provisions were separated into two categories, freeze and dry. The linear regressions for HULL, freeze provisions, and dry provisions, and derivation of the stocking objectives for the Point Estimate Model are provided in Appendix G. Below are the resulting equations for the monthly stocking objectives for provisions and HULL when an end of the month resupply is scheduled.

$$\text{Freeze Provisions} = (M_{n+2} \times \overline{AMD_i}) + (M_{n+1} \times 1.57 \times \overline{AMD_i}) = 2.57AMD \qquad \{17\}$$

$$\text{Dry Provisions} = (M_{n+2} \times \overline{AMD_i}) + (M_{n+1} \times 1.93 \times \overline{AMD_i}) = 2.93AMD \qquad \{18\}$$

$$\text{HULL items} = (M_{n+2} \times \overline{AMD_i}) + (M_{n+1} \times 2.10 \times \overline{AMD_i}) = 3.10AMD \qquad \{19\}$$

The same simulation is used to compare the performance of four models (2.1 AMD, Modified AMD, Point Estimate, and Lognormal) in setting Sixth Fleet inventory levels for provisions and HULL. A twelve month data base is used to compute AMD values for all models. Provisions are divided into two categories, freeze (including chill) provisions and dry provisions. The same assumptions used in the QCOG simulation are applicable. MOEs, input, and output parameters remain the same. Table 6 provides the average MOE values achieved by each model.

The simulation results for provisions and HULL are similar to those found for QCOG. Again, the Lognormal and Point Estimate Models clearly outperform the 2.1 AMD and Modified AMD Models, increasing monthly effectiveness by four to five percentage points and increasing safety stock effectiveness by 20 to 30 percentage points.

Table 6. SIMULATION RESULTS FOR PROVISIONS AND HULL

Average MOE Values from Six Month Simulation					
Item	**MOE**	**2.1 AMD**	**Modified 2.1 AMD**	**Point Estimate**	**Lognormal**
Dry Provisions	Monthly Effectiveness	0.932	0.946	0.983	0.987
	Safety Stock Effectiveness	0.668	0.669	0.937	0.936
	Inventory Volume (MT)	1345	1419	1966	1929
Freeze Provisions	Monthly Effectiveness	0.941	0.949	0.980	0.989
	Safety Stock Effectiveness	0.602	0.588	0.856	0.901
	Inventory Volume (MT)	768	808	983	995
HULL	Monthly Effectiveness	0.949	0.953	0.984	0.988
	Safety Stock Effectiveness	0.738	0.703	0.952	0.956
	Inventory Volume (MT)	541	570	845	826

F. WILL IT FIT?

In addition to providing significant increases in monthly and safety stock effectiveness, stocking using the Lognormal and Point Estimate Models significantly increases inventory levels. The question "will it fit?" can be answered only by the on station AFS. The determination of storage capacities is a dynamic problem. Often the asset with the largest storage capacity available to the AFS (Military Sealift Command T-AFS) is available only for one or two cycles. However, for the most part, the schedules of the CLF ships that provide services to LOGREP customers are known and allow accurate calculations of total Sixth Fleet storage capacities.

Both the Lognormal and Point Estimate Models can compute the probability that future demand will be less than or greater than a given quantity of inventory. These probabilities can be most useful to the inventory manager concerned with constrained space. Knowing the probability that demand will exceed inventory allows the AFS to ensure a level of support. The probability that demand will not exceed a specified quantity of inventory provides the inventory manager information on possible maximum inventory levels at the end of a cycle. This can be especially useful for provision and HULL items when the Sixth Fleet experiences a reduction in CLF assets and those ships leaving the Mediterranean download their inventories to remaining CLF ships. In this

scenario the Lognormal and Point Estimate Models can be used to determine the probability of an inventory exceeding constrained storage capacity (QCOG security storage or provision freezer storage) at the end of a cycle.

The stocking objectives for the Point Estimate Model provides insight into the feasibility of stocking the inventory levels generated by the Lognormal and Point Estimate Models. The stocking rules for the Point Estimate Model range from 2.5 AMD to 3.1 AMD. (See Appendix G.) Inventory levels of this size are not new to the Sixth Fleet. Typically the beginning of the month inventory objective for the four months when a resupply is not scheduled at the end of the LOGREP cycle is 3.1 AMD. When storage capacity exists for a 3.1 AMD beginning of the month inventory it also exists for inventories generated by the Point Estimate and Lognormal Models.

VII. SUMMARY

A. FINDINGS

Tersine states that a good forecast provides not only a single best estimate of demand, but also an estimate of the magnitude of likely deviations as a guide to the comparative reliability of the forecast [Ref. 3: p. 210]. Inventory theory and the laws of probability point to an item's standard deviation as the best measure to protect against demand deviations. Computing power available today can calculate standard deviations as quickly as an AMD. Even on a hand held calculator, data entered to compute a mean will, with one extra push of a button, yield the standard deviation.

Although the current method of determining inventory levels is straightforward and stocking objectives required by it are easily calculated, the current method can also be improved. Although customer support (monthly effectiveness) during the six month simulation exceeded 88% for all models, the results for the measure of performance against COMNAVSURFLANT's goal of one AMD on hand at all times were not as positive. The 2.1 AMD Model and Modified AMD Model performed poorly, meeting the COMNAVSURFLANT goal on average, less than 70% of the time. The results of the simulation for the 2.1 AMD Model should be viewed as the lower bound for what is actually achieved in the Sixth Fleet. Inventory managers spend considerable resources reviewing historical data, communicating with customer ships, and optimizing storage capacities. These efforts improve effectiveness. The results of this thesis provide inventory managers with a method to obtain a better management base.

Two shortcomings of the 2.1 AMD Model, AMD determination and safety stock computations, were identified and analyzed. Data analysis identified the lognormal distribution as the underlying distribution for QCOG demand. The lognormal distribution also fit the demand of a random sample of 50 provision and HULL items. Intuitively the positively skewed lognormal distribution properly explains and predicts the spikes in demand that concern every Sixth Fleet inventory manager. Improvements to AMD calculations, motivated by COMSERVFORSIXTHFLT and tested by Concord, were combined with improvements, based on the use of standard deviations, to the safety stock calculations. Two alternative models were developed, the Lognormal Model and Point Estimate Model.

The conclusions of the thesis are summarized below:

- SUADPS and LOTUS demand records, measuring the same monthly demand, do not agree. When there is disagreement between the two data bases, the SUADPS records for freeze provisions and HULL items (and most likely for dry provisions) tend to understate demand.
- The underlying distribution for provisions, HULL, and QCOG is unimodal and positively skewed. The theoretical lognormal distribution was selected as the distribution providing the best fit to the empirical data.
- The Modified AMD Model did not provide improved customer support over what was already achieved by the 2.1 AMD Model.
- Improved performance over the 2.1 AMD and Modified AMD Models is achieved by the Point Estimate Model, but not at the expected 95% level of support.
- The Lognormal provided the best support relative to the measures of effectiveness for customer support (monthly effectiveness) and COMNAVSURFLANT's one AMD goal (safety stock effectiveness).
- The Lognormal Model and Point Estimate Model provide:
    1. The inventory manager a method to compute inventory levels based on a desired support level of COMNAVSURFLANT's one AMD goal.
    2. The inventory manager a method to compute the probability of specific inventory levels at the end of a LOGREP cycle.
    3. COMNAVSURFLANT and COMSERVFORSIXTHFLT a method to project the impact of changes in force levels on the effectiveness of the AFS.
- The feasibility of stowing the increased inventory levels, generated by the Lognormal Model and Point Estimate Model, must be determined by the on station AFS. The Point Estimate Model provides a guide to the relative size of these increases because its stocking objective is in terms of AMD.

The Point Estimate Model was developed to provide those familiar with the current method of managing Sixth Fleet inventories a model that offers improved performance using the same arithmetic. The Lognormal Model outperformed the other models during the six month simulation. It provided the best monthly effectiveness and safety stock effectiveness. Additionally, the Lognormal Model's safety stock effectiveness was close to its 95% expected value, determined by the level of support. Although there is a trade off between accuracy and simplicity when implementing a model, with the computer resources available today, accuracy should be the most important criterion for a resupply model. In managing Sixth Fleet inventories, the best and most accurate results will be achieved with the Lognormal Model. This model, then, should be used.

B. FUTURE RESEARCH

The importance of accurate historical demand for management of Sixth Fleet provision, HULL, and QCOG inventories can not be over emphasized. It is the critical input for the inventory models currently used and for those proposed in this thesis. Before management procedures are standardized, the historical demand data base should be standardized. The use of inaccurate SUADPS data to determine inventory levels is an accident waiting to happen. This should be a priority area for future research.

The Point Estimate Model and Lognormal Model do not attempt to explain the causes for spikes in demand. These two models acknowledge the existence of variable demand and provide a method to meet that demand. The two basic types of forecasting techniques are those based almost entirely on past demand observations and those that rely heavily on events other than historical demand. Each AFS/TAFS has its own procedure for forecasting demand, but all attempt to combine the two techniques, looking at both historical demand and at a multitude of external factors. USS San Diego (AFS-6) identified the following external factors to be considered when analyzing the causes of spikes in demand [Ref. 9]:

- Seasonality of item.
- Item availability and substitutability.
- Inport versus underway days.
- Differences in each ship's cycle menu.

San Diego's list provides an excellent starting point for future research.

The only maintenance the Lognormal Model requires is a periodic review to validate the *fit* of the lognormal distribution. The Point Estimate Model offers many possibilities for future research. The stocking objectives that the Point Estimate Model generates depend on the slope of the regression line. By performing regression on groups of items with similar ratios of standard deviation to mean, the inventory manager can further refine stocking objectives. However, because the slope of the regression line is sensitive to outliers, changes to the stocking objectives should be carefully analyzed. In the final analysis, the best results for the Point Estimate Model would be achieved if each item's ratio of standard deviation to mean were computed. However, computing a ratio for each item would yield the same stocking levels generated by the Lognormal Model: in short, the Point Estimate Model would be extended to equivalence with the Lognormal Model.

APPENDIX A. MONTHLY NUMBER OF SAILORS SUPPORTED

Table 7. CREW SIZES

Crew Size Estimates by Ship Type (Hull Number)	
Ship Type	Crew Size
AD (18 class)	780
AD (37 class)	1260
AE	360
AFS	430
AGF	540
AO (98 class)	370
AO (177 class)	180
AOE	560
AOR	440
AR	750
ARS	100
AS	1160
BB	1390
CG	360
CGN	570
CV (small)	4800
CV (large)	5300
DD	280
DDG	350
FF	260
FFG	270
LCC	800
LHA	2180
LPH	1500
LPD	1000
LSD	590
LST	520
LKA	710

Table 8. SIXTH FLEET POPULATION BY MONTH

Number of Sailors Supported		
Month	Ships	Sailors
June 1986	42	32470
July 1986	33	24570
August 1986	33	24170
September 1986	34	24550
October 1986	34	26240
November 1986	27	18440
December 1986	23	16480
January 1987	35	25450
Febuary 1987	37	26040
March 1987	26	17380
April 1987	25	16890
May 1987	36	26070
June 1987	not	available
July 1987	30	17850
August 1987	24	14590
September 1987	27	15570
October 1987	47	30980
November 1987	30	19240
December 1987	23	16550
January 1988	26	16220
Febuary 1988	30	19250
March 1988	42	31400
April 1988	26	16920
May 1988	36	25390
June 1988	28	17880
July 1988	26	17880
August 1988	53	33950
September 1988	26	17210

APPENDIX B. TEN MONTH INVENTORY REVIEW

Table 9. SUADPS INVENTORY REVIEW

Unit of Issue is Pounds EVENT	Q31		Q40		S92	
	receipts	issues	receipts	issues	receipts	issues
1-88 Beginning Inventory	92106		11342		3738	
1-88 Demand		6154		860		396
2-88 Callout	31550		3350		552	
2-88 Supplemental	1500		950		336	
2-88 Demand		4385		690		252
3-88/4-88 Callout	90550		11000		3696	
3-88 Supplemental	0		0		0	
3-88 Demand		25949		912		1764
Milwaukee Deploys	30000		7000		960	
4-88 Supplemental	0		0		984	
4-88 Demand		11597		250		144
5-88 Callout	36650		8050		3096	
5-88 Demand		37635		848		1044
6-88 Callout	54900		4900		1200	
6-88 Demand		11730		2736		480
7-88 Callout	14100		0		0	
7-88 Supplemental	0		0		0	
7-88 Demand		37485		4738		2940
8-88/9-88 Callout	88250		9500		3024	
8-88 Supplemental	47050		3350		3120	
8-88 Demand		20955		2025		1548
9-88 Demand		23025		1477		708
10-88 Callout	33605		2968		1800	
10-88 Supplemental	0		2400		240	
TOTALS	428155	178915	53468	14536	19008	9279
10/1/88 Ending Inventory	86390		12382		3894	
Reconstructed Inventory	341346		50274		13467	

Table 10. LOTUS INVENTORY REVIEW

Unit of Issue is Pounds EVENT	Q31		Q40		S92	
	receipts	issues	receipts	issues	receipts	issues
1-88 Beginning Inventory	92106		11342		3738	
1-88 Demand		36369		7455		1440
2-88 Callout	31550		3350		552	
2-88 Supplemental	1500		950		336	
2-88 Demand		42373		5036		1572
3-88/4-88 Callout	90550		11000		3696	
3-88 Supplemental	0		0		0	
3-88 Demand		61445		5072		2532
Milwaukee Deploys	30000		7000		960	
4-88 Supplemental	0		0		984	
4-88 Demand		19760		2994		864
5-88 Callout	36650		8050		3096	
5-88 Demand		54125		3740		1560
6-88 Callout	54900		4900		1200	
6-88 Demand		33625		4413		2172
7-88 Callout	14100		0		0	
7-88 Supplemental	0		0		0	
7-88 Demand		38425		5088		2880
8-88/9-88 Callout	88250		9500		3024	
8-88 Supplemental	47050		3350		3120	
8-88 Demand		63695		11455		2754
9-88 Demand		37200		4903		2190
10-88 Callout	33605		2968		1800	
10-88 Supplemental	0		2400		240	
TOTALS	428155	387017	53468	50156	19008	17964
10/1/88 Ending Inventory	86390		12382		3894	
Reconstructed Inventory	133244		14654		4782	

APPENDIX C. QCOG ITEM IDENTIFICATION

Table 11. QCOG ITEM IDENTIFICATION

Item Number	Nomenclature	Unit of Issue	Unit Cost	Unit Pack	ft^3 per Case
0001	Baby Ruth	BR	0.25	288	1.48
0002	Butterfinger	BR	0.25	288	0.83
0004	Hershey Almond	BR	0.25	432	1.00
0005	Hershey Milk	BR	0.25	432	0.78
0006	Lifesavers	PG	0.23	500	0.83
0007	M&M Peanut	BG	0.25	360	1.32
0008	M&M Plain	BG	0.25	360	1.08
0009	Milky Way	BR	0.25	360	1.39
0010	Snickers	BR	0.25	360	1.27
0011	Bit-O-Honey	BR	0.25	288	1.03
0012	Kraft Carmel	PG	0.17	144	0.37
0013	Chuckles	PG	0.23	288	1.15
0014	Tootsie Roll	BR	0.24	288	0.79
0015	Licorice	BR	0.17	144	0.71
0016	Reeses Pieces	BR	0.25	432	1.80
0017	Musketeers	BR	0.25	360	1.85
0020	Jumbo Block	BR	0.25	288	0.98
0021	Fruit Chewies	PG	0.25	360	1.08
0022	Nestles Crunch	BR	0.25	360	0.78
0023	Kit Kat	BR	0.25	432	1.55
0131	Cashews	EA	2.33	12	0.27
0132	Mixed Peanuts	EA	1.28	12	0.27
0133	Peanuts	EA	0.78	12	0.27
0134	Spanish Nuts	EA	0.78	12	0.36
0151	Baked Beans	CN	0.28	24	0.40
0152	Potatoe Tins	EA	0.52	36	1.80
0154	Beef Jerky	BG	0.11	144	0.26
0155	Pepperoni	BG	0.14	288	0.89
0156	Vienna Sausages	CN	0.39	48	0.48

Item Number	Nomenclature	Unit of Issue	Unit Cost	Unit Pack	ft^3 per Case
0158	Potatoe Chips	EA	1.07	36	1.80
0159	Pretzels	EA	0.82	12	0.60
0160	Cookies	EA	1.30	24	1.22
0161	Chocolate Pudding	EA	0.84	12	0.45
0162	Vanilla Pudding	EA	0.84	12	0.45
0301	Camels	CT	4.80	60	2.55
0305	Marlboro	CT	4.80	60	3.03
0308	Salem	CT	4.80	60	3.03
0310	Winston	CT	4.80	60	3.03
0312	Kool	CT	3.92	30	1.44
0318	Winston Lights	CT	4.80	60	3.03
0319	Merit	CT	4.80	60	2.42
0320	Marlboro Lights	CT	4.80	60	2.52
0321	Salem Lights	CT	4.80	60	2.52
0322	Class A	CT	1.90	60	2.60
0327	Tiparillo	PG	0.37	960	3.67
0328	Panatella	PG	0.83	500	3.00
0331	Jewels	PG	0.54	400	2.30
0351	Middleton	PG	0.58	144	1.50
0360	Borkum Riff	PG	0.96	144	1.25
0361	Copenhagen	CN	0.93	180	3.12
0362	Skoal	CN	0.93	180	3.12
0379	Matches	PG	0.25	50	1.36
0384	Lighter Fluid	CN	0.48	24	0.21
0385	Butane Fluid	CN	0.82	72	0.63
0386	Lighters	EA	0.44	72	0.31
0403	Envelopes	PG	0.52	24	0.80
0407	Tablet	EA	0.37	72	0.50
0409	Envelopes	PG	0.40	24	0.90
0507	Cards	EA	0.40	144	0.57
0509	Comb	EA	0.04	432	3.60
0520	Mug	EA	1.08	72	1.30
0521	Padlock	EA	1.35	72	0.48
0523	Shoe Polish	CN	0.49	144	0.63
0531	Shower Shoes	PR	0.38	72	6.80

Item Number	Nomenclature	Unit of Issue	Unit Cost	Unit Pack	ft^3 per Case
0533	Cassettes	EA	0.69	100	0.78
0607	Trac II Cartridge	PG	2.10	72	0.34
0608	Atra Cartridge	PG	2.10	72	0.17
0621	Gillete Shave Cream	EA	1.38	24	0.51
0623	Noxema Shave Cream	EA	1.25	24	0.60
0625	Rise Shave Cream	EA	1.54	24	0.47
0626	Edge Shave Cream	EA	1.54	12	0.26
0641	Colgate	EA	0.87	36	0.35
0642	Crest	EA	0.87	36	0.35
0645	Close Up	EA	1.23	24	0.50
0646	Aim	EA	1.23	24	0.50
0661	Right Guard	EA	1.55	24	0.37
0666	Speed Stick	EA	1.27	24	0.22
0667	Old Spice Stick	EA	1.71	24	0.292
0671	Aqua Velva	EA	1.71	24	0.52
0672	Skin Bracer	EA	1.62	24	0.57
0673	Old Spice	EA	2.75	24	0.54
0682	Mennen	EA	1.87	24	0.58
0683	Quinsana	EA	1.69	12	0.14
0694	Trac II Razors	EA	3.20	36	1.04
0696	Atra Razors	SE	2.97	36	0.80
0697	Good News	PG	0.57	144	0.53
0703	Prell	TU	1.45	12	0.12
0704	Head & Shoulders	TU	2.79	12	0.26
0711	Camay	EA	0.73	72	0.49
0712	Dial	EA	0.38	72	0.36
0715	Safeguard	EA	0.40	72	0.36
0716	Zest	EA	0.37	72	0.38
0717	Irish Spring	EA	0.38	48	0.26
0718	Coast	EA	0.57	72	0.50
0732	Vitalis	EA	2.17	36	0.46
0738	Dry Look Hair Spray	EA	2.07	24	0.41
0751	Listerine	EA	1.32	24	0.72
0752	Soap Box	EA	0.18	144	0.60
0755	Skin Cream	EA	1.25	48	0.58

Item Number	Nomenclature	Unit of Issue	Unit Cost	Unit Pack	ft^3 per Case
0756	Tooth Brush Holder	EA	0.14	144	0.50
0760	Coppertone	EA	2.73	12	0.16
0765	Conditioner	EA	0.98	72	0.49
0772	Scope	EA	1.26	12	0.36
0773	Tooth Brush	EA	0.30	12	0.05
0774	Battery AA	EA	0.16	144	0.68
0775	Battery C	EA	0.28	72	0.99
0776	Battery D	EA	0.42	72	1.25
0777	Battery 9 Volt	EA	0.55	48	0.47
0780	Floss	EA	0.77	36	0.26
0791	Ramses	PG	0.45	48	0.09
0793	Fourex	BX	1.88	48	0.11
0906	Popcorn	EA	4.67	4	1.20
0907	Popcorn Bags	CS	9.00	6	3.50
0912	Tomato Juice	CN	0.33	24	0.52
0913	Hawaiin Punch	PG	1.76	8	0.78
1100	Small Shirt	EA	4.94	60	2.40
1101	Medium Shirt	EA	5.77	60	2.40
1102	Large Shirt	EA	5.77	60	2.40
1103	XLarge Shirt	EA	5.77	60	2.40
1115	Trouser 28	EA	7.00	48	2.00
1116	Trouser 29	EA	8.10	48	2.00
1117	Trouser 30	EA	7.75	48	2.00
1118	Trouser 31	EA	7.75	48	2.00
1119	Trouser 32	EA	7.75	48	2.00
1120	Trouser 33	EA	7.75	48	2.00
1121	Trouser 34	EA	7.75	48	2.00
1122	Trouser 36	EA	7.00	48	2.00
1123	Trouser 38	EA	7.75	48	2.00
1124	Trouser 40	EA	8.10	48	2.00
1125	Trouser 42	EA	8.10	48	2.00

APPENDIX D. DATA ANALYSIS RESULTS

Table 12. UNIVARIATE ANALYSIS RESULTS

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
0001	issues	0	27	8.5	10.77	8.50	0.42
	quantity	0	7.84	2.63	2.68	2.13	0.69
0002	issues	2	23	10	10.91	5.53	0.73
	quantity	0.31	3.84	1.36	1.49	0.84	1.21
0004	issues	2	22	8.5	9.73	4.81	0.65
	quantity	0.16	2.99	1.04	1.23	0.76	0.85
0005	issues	0	12	6.5	6.45	3.85	0.09
	quantity	0	2.51	0.75	0.79	0.60	1.15
0006	issues	1	19	5	5.73	3.92	1.94
	quantity	0.13	1.67	0.47	0.51	0.34	1.92
0007	issues	5	54	21.5	23.64	11.35	0.77
	quantity	0.87	9.77	4.82	5.01	2.47	0.16
0008	issues	2	45	17.5	18.77	10.66	0.79
	quantity	0.47	5.46	2.10	2.85	1.72	0.23
0009	issues	2	18	7	8.41	4.48	0.70
	quantity	0.48	6.43	1.43	1.97	1.47	1.59
0010	issues	7	55	25	27.00	11.69	0.34
	quantity	1.92	11.58	6.52	6.13	2.64	0.06
0011	issues	3	24	8	9.45	5.49	1.28
	quantity	0.36	3.41	1.28	1.57	0.94	0.57
0012	issues	1	19	5.5	5.68	3.94	1.61
	quantity	0.04	1.38	0.31	0.38	0.34	1.78
0013	issues	1	12	5	5.45	3.03	0.55
	quantity	0.14	1.98	0.56	0.69	0.45	1.09
0014	issues	1	15	5.5	6.23	3.58	0.60
	quantity	0.15	2.73	0.57	0.73	0.55	2.29
0015	issues	1	16	5	5.82	4.34	1.16
	quantity	0.08	3.68	0.49	0.98	1.06	1.33

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
0016	issues	5	31	12	13.36	5.88	1.24
	quantity	1.73	8.14	4.14	4.25	1.80	0.50
0017	issues	2	16	7	7.82	4.27	0.35
	quantity	0.23	6.02	2.05	2.43	1.30	0.90
0020	issues	1	14	4	5.00	3.37	2.49
	quantity	0.06	2.42	0.68	0.85	0.69	1.09
0021	issues	3	15	6	7.09	3.50	0.90
	quantity	0.30	2.22	0.79	0.99	0.57	0.78
0022	issues	1	20	9	9.14	5.01	0.40
	quantity	0.13	3.00	1.01	1.19	0.86	0.52
0023	issues	3	23	10	10.77	5.31	0.83
	quantity	0.96	6.11	1.93	2.21	1.30	1.65
0131	issues	2	28	9.5	11.41	6.79	0.91
	quantity	0.44	4.63	1.58	2.00	1.25	0.60
0132	issues	1	25	8.5	8.50	5.25	1.19
	quantity	0.21	3.62	1.13	1.40	0.89	1.02
0133	issues	2	16	6	6.82	3.89	0.96
	quantity	0.17	2.22	0.92	1.01	0.59	0.44
0134	issues	1	14	5	6.41	3.75	0.42
	quantity	0.12	5.30	1.17	1.55	1.34	1.58
0151	issues	1	13	6	6.05	3.36	0.35
	quantity	0.05	3.04	0.82	0.92	0.80	1.29
0152	issues	2	28	11	12.46	5.92	0.75
	quantity	1.23	27.82	9.56	10.46	7.09	0.93
0154	issues	3	17	8.5	8.77	4.41	0.55
	quantity	0.16	1.20	0.61	0.72	0.31	0.29
0155	issues	0	14	5	5.73	3.98	0.43
	quantity	0	1.99	1.00	0.97	0.64	0.17
0156	issues	3	21	9.5	9.73	5.03	0.79
	quantity	0.64	2.52	1.41	1.41	0.62	0.33
0158	issues	6	37	18	18.86	6.35	0.71
	quantity	6.36	36.08	17.77	19.91	9.06	0.35
0159	issues	5	38	15	16.41	7.98	0.85
	quantity	1.85	19.25	9.24	9.59	5.54	0.43

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
0160	issues	1	20	7	7.55	5.04	1.16
	quantity	0.19	11.22	4.13	4.47	3.05	0.83
0161	issues	3	19	7.5	8.27	4.58	0.85
	quantity	0.36	11.44	3.20	3.34	2.56	1.45
0162	issues	3	19	5.5	7.09	4.31	1.18
	quantity	0.27	15.45	1.91	2.87	3.21	3.06
0301	issues	0	13	2	3.50	3.00	1.60
	quantity	0	4.52	0.58	0.79	0.93	3.27
0305	issues	6	43	17.5	17.91	7.98	1.15
	quantity	6.86	41.22	19.24	19.77	8.87	0.75
0308	issues	1	8	4	4.36	2.28	0.18
	quantity	0.10	2.72	1.38	1.44	0.88	0.001
0310	issues	3	12	6	6.59	2.46	0.45
	quantity	0.68	6.70	2.85	3.02	1.51	0.47
0312	issues	1	22	7	8.18	5.40	0.80
	quantity	0.09	9.15	2.46	2.43	2.04	1.68
0318	issues	1	9	5	4.86	2.38	0.06
	quantity	0.19	4.44	1.80	1.99	1.20	0.41
0319	issues	1	11	6	5.36	2.52	0.40
	quantity	0.16	2.77	1.38	1.40	0.70	0.19
0320	issues	4	25	14	13.50	5.00	0.02
	quantity	2.05	16.35	5.39	6.25	3.25	1.51
0321	issues	1	14	4	5.59	3.79	0.83
	quantity	0.16	5.34	1.20	1.70	1.48	0.93
0322	issues	0	7	0	1.82	2.75	1.01
	quantity	0	7.93	2.47	1.25	2.39	0.53
0327	issues	0	3	1	0.95	0.90	0.49
	quantity	0	0.47	0.23	0.16	0.16	0.27
0328	issues	0	8	2	2.00	2.12	1.30
	quantity	0	0.84	0.25	0.27	0.27	0.85
0331	issues	0	4	1	1.50	1.26	0.58
	quantity	0	0.56	0.16	0.18	0.15	0.99
0351	issues	0	3	0	0.45	0.86	1.76
	quantity	0	1.37	0.10	0.09	0.30	1.77

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
0360	issues	0	5	0	0.77	1.31	2.26
	quantity	0	1.14	0.06	0.09	0.25	2.57
0361	issues	5	27	10	11.27	5.51	1.03
	quantity	1.75	9.24	5.11	5.23	1.87	0.23
0362	issues	2	18	7.5	7.50	4.35	0.64
	quantity	0.80	5.81	2.03	2.57	1.54	1.03
0379	issues	0	2	0	0.23	0.61	2.42
	quantity	0	2.79	0.21	0.15	0.61	0.70
0384	issues	0	14	4.5	5.09	3.74	0.88
	quantity	0	0.74	0.18	0.22	0.22	1.07
0385	issues	0	3	1	0.82	0.91	0.75
	quantity	0	0.17	0.05	0.04	0.05	0.99
0386	issues	0	9	4	4.27	2.43	0.30
	quantity	0	0.71	0.22	0.23	0.16	1.16
0403	issues	1	17	6	6.45	4.22	0.81
	quantity	0.18	15.93	1.94	2.81	3.44	2.78
0407	issues	0	14	6	5.82	4.23	0.12
	quantity	0	2.51	0.79	0.71	0.70	1.31
0409	issues	0	10	3	3.95	2.97	0.79
	quantity	0	6.51	1.59	2.34	2.15	0.52
0507	issues	0	11	4	3.82	2.74	0.77
	quantity	0	0.43	0.14	0.17	0.14	0.61
0509	issues	1	14	4	4.86	3.43	1.17
	quantity	0.15	3.81	0.74	1.01	0.91	1.76
0520	issues	0	11	2	2.32	2.59	1.80
	quantity	0	1.63	0.36	0.31	0.36	2.68
0521	issues	2	12	3.5	4.59	2.75	0.86
	quantity	0.05	1.51	0.17	0.29	0.33	2.65
0523	issues	1	10	6	5.32	2.32	0.14
	quantity	0.12	0.64	0.24	0.31	0.16	0.85
0531	issues	1	16	4	4.59	3.49	1.67
	quantity	0.39	9.54	2.85	3.48	2.76	0.72
0533	issues	1	28	13	14.18	6.87	0.26
	quantity	0.32	7.02	3.09	3.18	1.94	0.13

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
0607	issues	2	17	4.5	5.23	3.45	2.14
	quantity	0.04	0.87	0.15	0.26	0.23	1.40
0608	issues	3	20	5.5	7.45	4.90	1.55
	quantity	0.03	0.82	0.14	0.21	0.19	1.84
0621	issues	1	10	3	3.50	1.92	1.73
	quantity	0.05	39.64	0.47	2.52	8.53	4.21
0623	issues	1	10	3.5	4.32	2.73	0.72
	quantity	0.04	1.52	0.48	0.62	0.48	0.49
0625	issues	1	17	3	4.00	3.61	2.24
	quantity	0.06	1.77	0.29	0.44	0.41	1.78
0626	issues	1	11	3.5	4.59	2.77	1.08
	quantity	0.03	2.87	0.47	0.55	0.58	3.18
0641	issues	1	16	5	5.82	3.58	1.20
	quantity	0.08	1.85	0.48	0.58	0.48	1.32
0642	issues	3	24	8.5	9.73	5.80	1.20
	quantity	0.21	2.02	0.66	0.89	0.60	0.76
0645	issues	1	12	5	5.18	2.59	0.58
	quantity	0.15	2.74	0.70	0.90	0.66	1.40
0646	issues	1	10	5	4.82	2.50	0.32
	quantity	0.13	5.42	0.49	1.13	1.37	1.96
0661	issues	2	16	4	5.05	3.34	1.83
	quantity	0.61	2.43	0.46	0.67	0.64	1.48
0666	issues	1	15	6	6.23	3.48	0.97
	quantity	0.06	1.12	0.35	0.40	0.29	1.08
0667	issues	0	13	5	5.23	3.34	0.54
	quantity	0	1.40	0.36	0.40	0.33	1.89
0671	issues	0	6	1	1.50	1.82	1.12
	quantity	0	0.84	0.12	0.20	0.28	0.49
0672	issues	0	8	1	1.68	2.10	1.44
	quantity	0	2.10	0.28	0.25	0.47	2.50
0673	issues	0	7	1.5	2.23	2.09	0.78
	quantity	0	2.33	0.22	0.37	0.61	1.95
0682	issues	1	13	3	3.77	2.91	1.64
	quantity	0.07	1.93	0.29	0.46	0.46	1.91

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
0683	issues	1	15	5	5.55	3.63	1.23
	quantity	0.03	2.32	0.19	0.38	0.55	2.68
0694	issues	0	6	1.5	2.23	1.80	0.86
	quantity	0	3.51	0.32	0.57	0.80	2.42
0696	issues	0	6	2	2.77	1.77	0.30
	quantity	0	4.90	0.42	0.66	1.07	3.16
0697	issues	1	11	4	4.64	2.30	1.06
	quantity	0.10	1.00	0.25	0.30	0.21	1.96
0703	issues	1	21	8.5	8.82	4.67	0.88
	quantity	0.25	2.16	0.60	0.72	0.48	1.79
0704	issues	4	15	8	8.68	3.75	0.29
	quantity	0.22	4.23	1.12	1.27	0.92	1.71
0711	issues	0	13	3	3.64	3.02	1.43
	quantity	0	1.39	0.29	0.36	0.33	1.52
0712	issues	0	11	5	5.41	2.72	0.21
	quantity	0	8.94	0.29	0.74	1.89	4.08
0715	issues	3	18	7.5	8.18	4.07	0.67
	quantity	0.10	1.23	0.55	0.53	0.29	0.54
0716	issues	2	10	5	4.91	2.11	0.52
	quantity	0.06	1.01	0.32	0.34	0.22	1.48
0717	issues	3	25	6.5	8.55	5.42	1.56
	quantity	0.14	1.03	0.73	0.59	0.31	0.15
0718	issues	2	26	8	8.41	5.59	1.73
	quantity	0.18	2.08	0.75	0.79	0.48	0.99
0732	issues	0	3	1	0.73	0.77	1.14
	quantity	0	0.26	0.03	0.03	0.06	2.20
0738	issues	0	3	1	1.05	0.84	0.40
	quantity	0	1.14	0.05	0.12	0.27	2.37
0751	issues	3	10	6.5	6.09	2.39	0.02
	quantity	0.22	2.89	0.94	1.06	0.75	0.96
0752	issues	0	11	5	4.91	3.37	0.27
	quantity	0	0.85	0.25	0.27	0.22	1.00
0755	issues	1	10	2.5	3.50	2.65	0.79
	quantity	0.02	0.85	0.27	0.29	0.21	0.77

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
0756	issues	0	7	2	2.55	2.04	0.64
	quantity	0	0.53	0.06	0.11	0.14	1.85
0760	issues	0	7	1.5	1.95	2.28	0.80
	quantity	0	0.40	0.10	0.08	0.11	0.92
0765	issues	0	7	1	1.59	1.76	1.50
	quantity	0	0.21	0.07	0.07	0.06	0.62
0772	issues	2	16	5	6.14	3.85	1.34
	quantity	0.25	4.16	0.79	1.08	0.96	1.85
0773	issues	0	11	4.5	5.05	2.61	0.49
	quantity	0	0.97	0.12	0.23	0.25	1.74
0774	issues	7	35	15.5	16.96	6.79	0.91
	quantity	1.65	15.59	6.92	7.07	3.95	0.46
0775	issues	1	17	9	9.18	4.49	0.14
	quantity	0.03	5.20	1.82	2.40	1.50	0.44
0776	issues	1	20	10	9.59	4.87	0.54
	quantity	0.52	7.60	2.03	2.63	2.01	1.31
0777	issues	0	6	1	1.50	1.82	1.02
	quantity	0	0.56	0.11	0.09	0.14	1.75
0780	issues	0	6	2	2.64	1.94	0.37
	quantity	0	0.54	0.17	0.15	0.13	1.32
0791	issues	0	6	1	1.91	1.74	0.75
	quantity	0	0.06	0.02	0.02	0.02	0.41
0793	issues	0	4	0	0.86	1.25	1.17
	quantity	0	0.08	0.03	0.01	0.02	0.78
0906	issues	0	5	2	1.55	1.44	0.45
	quantity	0	3.55	0.51	0.61	0.90	1.74
0907	issues	0	2	0	0.55	0.74	0.93
	quantity	0	22.33	0.21	1.12	4.86	2.47
0912	issues	1	9	3	3.55	2.37	0.98
	quantity	0.61	3.03	0.52	0.76	0.75	1.38
0913	issues	1	19	7	6.73	4.31	0.82
	quantity	0.43	71.40	9.15	15.98	18.63	1.55
1100	issues	0	6	2	2.00	1.72	0.46
	quantity	0	1.15	0.29	0.30	0.34	1.29

Item #	Category	Range		Median	Mean	Std Dev	Skewness
		Min	Max				
1101	issues	1	10	4	4.59	2.46	0.45
	quantity	0.11	3.11	0.72	0.90	0.71	1.85
1102	issues	1	10	4	4.09	2.14	0.69
	quantity	0.06	1.91	0.59	0.66	0.40	1.33
1103	issues	0	8	1.5	2.09	2.07	1.60
	quantity	0	1.07	0.19	0.21	0.25	1.93
1115	issues	0	4	0	0.86	1.21	1.26
	quantity	0	0.21	0.11	0.05	0.07	0.24
1116	issues	0	4	0	0.82	1.14	1.35
	quantity	0	0.30	0.09	0.05	0.08	1.03
1117	issues	0	10	2	2.32	2.61	1.59
	quantity	0	0.66	0.15	0.16	0.19	1.34
1118	issues	0	8	1	1.50	1.85	2.12
	quantity	0	0.52	0.13	0.10	0.12	2.11
1119	issues	0	8	2.5	2.86	2.34	0.72
	quantity	0	0.75	0.19	0.21	0.19	1.60
1120	issues	0	4	1	1.41	1.30	1.30
	quantity	0	0.29	0.13	0.09	0.09	0.51
1121	issues	0	10	2	2.50	2.37	1.55
	quantity	0	0.60	0.21	0.19	0.15	1.26
1122	issues	0	4	2	1.64	1.18	0.02
	quantity	0	0.36	0.16	0.12	0.10	0.47
1123	issues	0	8	0.5	1.36	2.11	1.95
	quantity	0	0.58	0.06	0.09	0.16	1.19
1124	issues	0	2	0	0.41	0.73	1.43
	quantity	0	0.19	0.07	0.02	0.05	0.27
1125	issues	0	2	0	0.36	0.73	1.63
	quantity	0	0.14	0.08	0.02	0.04	0.11

APPENDIX E. DISTRIBUTION FITTING

Table 13. DISTRIBUTION FITTING RESULTS

Kolmogorov-Smirnov Goodness of Fit Testing			
Item #	Data Points	Significance Levels	
		Gamma	Lognormal
0001	19	0.99909	0.89243
0002	21	0.91262	0.97212
0004	21	0.99996	0.99625
0005	20	0.86002	0.49053
0006	21	0.99761	0.96156
0007	21	0.92405	0.70063
0008	21	0.73369	0.63826
0009	21	0.90740	0.99857
0010	21	0.81729	0.66553
0011	21	0.92038	0.90908
0012	21	0.92929	0.57191
0013	21	0.99188	0.91924
0014	21	0.91435	0.92318
0015	21	0.74736	0.99576
0016	21	0.99781	0.99855
0017	21	0.72401	0.43420
0020	21	0.98922	0.85145
0021	21	0.85257	0.67880
0022	21	0.93554	0.96033
0023	21	0.33615	0.59844
0131	21	0.97966	0.91605
0132	21	0.99583	0.97651
0133	21	0.97915	0.96728
0134	21	0.99367	0.96250
0151	21	0.99383	0.80266
0152	21	0.97815	0.97451
0154	21	0.93830	0.95768
0155	19	0.91780	0.90111

Kolmogorov-Smirnov Goodness of Fit Testing			
Item #	Data Points	Significance Levels	
		Gamma	Lognormal
0156	21	0.63740	0.65363
0158	21	0.80937	0.79535
0159	21	0.92217	0.94362
0160	21	0.99129	0.81855
0161	21	0.96804	0.75947
0162	21	0.60398	0.57068
0301	20	0.71349	0.97858
0305	21	0.97978	0.85884
0308	21	0.60321	0.64409
0310	21	0.96193	0.75617
0312	21	0.77738	0.51387
0318	21	0.91344	0.64522
0319	21	0.98277	0.79118
0320	21	0.99171	0.99972
0321	21	0.73799	0.70003
0322	8	-	-
0327	14	0.89794	0.57194
0328	15	0.56003	0.73382
0331	17	0.27438	0.42128
0351	6	-	-
0360	10	-	-
0361	21	0.80809	0.63590
0362	21	0.68347	0.93345
0379	3	-	-
0384	19	0.87417	0.95440
0385	11	0.78349	0.85275
0386	20	0.96441	0.83392
0403	21	0.95068	0.85387
0407	18	0.94625	0.73091
0409	20	0.27664	0.23718
0507	19	0.94068	0.97526
0509	21	0.88671	0.99994
0520	16	0.65389	0.89075

Kolmogorov-Smirnov Goodness of Fit Testing			
Item #	Data Points	Significance Levels	
		Gamma	Lognormal
0521	21	0.27033	0.59009
0523	21	0.59384	0.77467
0531	21	0.94544	0.67185
0533	21	0.53247	0.29005
0607	21	0.21644	0.48619
0608	21	0.89434	0.99945
0621	21	*0.02497	0.64553
0623	21	0.83955	0.56228
0625	21	0.98660	0.99790
0626	21	0.86972	0.95796
0641	21	0.61255	0.83285
0642	21	0.72451	0.95879
0645	21	0.90736	0.97743
0646	21	0.31300	0.52488
0661	21	0.59889	0.91874
0666	21	0.89886	0.98943
0667	20	0.68432	0.60824
0671	13	0.50971	0.48634
0672	13	0.71710	0.97354
0673	16	0.72187	0.95669
0682	21	0.86005	0.99989
0683	21	0.27845	0.59024
0694	19	0.90783	0.77535
0696	20	0.54427	0.85598
0697	21	0.83465	0.99481
0703	21	0.37825	0.67646
0704	21	0.94906	0.98379
0711	20	0.99997	0.93555
0712	20	*0.01251	0.39001
0715	21	0.89564	0.70106
0716	21	0.88953	0.97190
0717	21	0.21394	0.16902
0718	21	0.99850	0.95645

Kolmogorov-Smirnov Goodness of Fit Testing			
Item #	Data Points	Significance Levels	
		Gamma	Lognormal
0732	13	0.13854	0.37331
0718	15	0.08368	0.45228
0751	21	0.85315	0.82309
0752	20	0.61086	0.26381
0755	21	0.68536	0.32032
0756	18	0.32383	0.80627
0760	11	0.98470	0.94822
0765	16	0.94929	0.93375
0772	21	0.49712	0.88688
0773	20	0.31881	0.53545
0774	21	0.95821	0.73412
0775	21	0.80016	0.31633
0776	21	0.97165	0.99938
0777	12	0.94269	0.90369
0780	19	0.66652	0.36339
0791	16	0.72588	0.83540
0793	8	-	-
0906	14	0.54815	0.89008
0907	9	-	-
0912	21	0.57509	0.62156
0913	21	0.92905	0.88707
1100	15	0.65690	0.94382
1101	21	0.41748	0.73413
1102	21	0.90495	0.78539
1103	18	0.92763	0.57239
1115	10	-	-
1116	10	-	-
1117	15	0.94560	0.98279
1118	14	0.86649	0.39504
1119	18	0.95699	0.99285
1120	14	0.91942	0.71777
1121	18	0.99673	0.89346
1122	16	0.68157	0.44224

Kolmogorov-Smirnov Goodness of Fit Testing			
Item #	Data Points	Significance Levels	
		Gamma	Lognormal
1123	11	0.84452	0.90409
1124	6	-	-
1125	5	-	-

APPENDIX F. DERIVATION OF POINT ESTIMATE MODEL

The Point Estimate Model is applicable to provisions, HULL, and QCOG items and is derived from the lognormal distribution and from the linear relationship between the mean and standard deviation for these items. The lognormal distribution provides:

$$\text{Sample Mean } = \overline{\mu} = e^{(\hat{\mu} + \frac{\hat{\sigma}^2}{2})}$$

$$\text{Sample Variance } = \overline{\sigma}^2 = e^{(2\hat{\mu} + \hat{\sigma}^2)}\left(e^{\hat{\sigma}^2} - 1\right)$$

$$\text{Sample Log Mean } = \hat{\mu} = \left(\frac{1}{n}\right)\sum_{i=1}^{n} \ln x_i$$

$$\text{Sample Log Variance } = \hat{\sigma}^2 = \left(\frac{1}{n-1}\right)\sum_{i=1}^{n}(\ln x_i - \hat{\mu})^2$$

Since the $\ln x_i$ are normally distributed, $N(\hat{\mu}, \hat{\sigma}^2)$, a level of support can be determined from the sample log mean and multiples of the sample log standard deviation:

$$\text{Level of Support} = 1 - \text{P(Stockout)} = \text{P}(X \leq \hat{\mu} + b(\hat{\sigma}))$$

At a 95% level of support (b = 1.65) the stocking objective per sailor supported for the Lognormal Model is:

$$\text{Stocking Objective} = AMD + e^{(\hat{\mu} + 1.65(\hat{\sigma}))}$$

The slope of the linear regression line (standard deviation on to the mean) provides a relationship that can be manipulated to yield a point estimate for the sample log standard deviation. From the linear regression:

$$\frac{\overline{\sigma}}{\overline{\mu}} = \frac{\left(e^{(2\hat{\mu} + \hat{\sigma}^2)}\left(e^{\hat{\sigma}^2} - 1\right) \right)^{0.5}}{e^{(\hat{\mu} + \frac{\hat{\sigma}^2}{2})}}$$

$$\frac{\overline{\sigma}}{\overline{\mu}} = \left(e^{\hat{\sigma}^2} - 1\right)^{0.5}$$

Solving for $\hat{\sigma}$:

$$\hat{\sigma} = \left(\ln \left(\left(\frac{\overline{\sigma}}{\overline{\mu}} \right)^2 + 1 \right) \right)^{0.5}$$

For the QCOG regression $\frac{\overline{\sigma}}{\overline{\mu}} = 0.601$ which provides a point estimate for $\hat{\sigma}$ equal to 0.5545.

Substituting the point estimate for $\hat{\sigma}$ into the stocking objective equation for the Lognormal Model at a 95% level of support provides:

$$\text{Stocking Objective } = AMD + e^{\hat{\mu}} \times e^{0.914} = AMD + 2.49e^{\hat{\mu}}$$

Multiplying $2.49e^{\hat{\mu}}$ by $\frac{e^{\frac{\hat{\sigma}^2}{2}}}{e^{\frac{\hat{\sigma}^2}{2}}}$ provides:

$$\text{Stocking Objective } = AMD + \frac{2.49}{\frac{e^{\hat{\sigma}^2}}{2}} \times e^{\hat{\mu}} e^{\frac{\hat{\sigma}^2}{2}}$$

Which can be rewritten as:

$$\text{Stocking Objective } = AMD + \frac{2.49}{\frac{e^{\hat{\sigma}^2}}{2}} \times e^{(\hat{\mu} + \frac{\hat{\sigma}^2}{2})}$$

Since the mean of the lognormal distribution is:

$$e^{(\hat{\mu} + \frac{\hat{\sigma}^2}{2})} = \overline{\mu} = AMD$$

and $\hat{\sigma}$ is known ($\hat{\sigma}$ = .554) the equation for the stocking objective for the Point Estimate Model reduces to:

$$\text{Stocking Objective } = AMD + 2.1AMD = 3.1AMD$$

APPENDIX G. LINEAR REGRESSIONS FOR POINT ESTIMATE MODEL

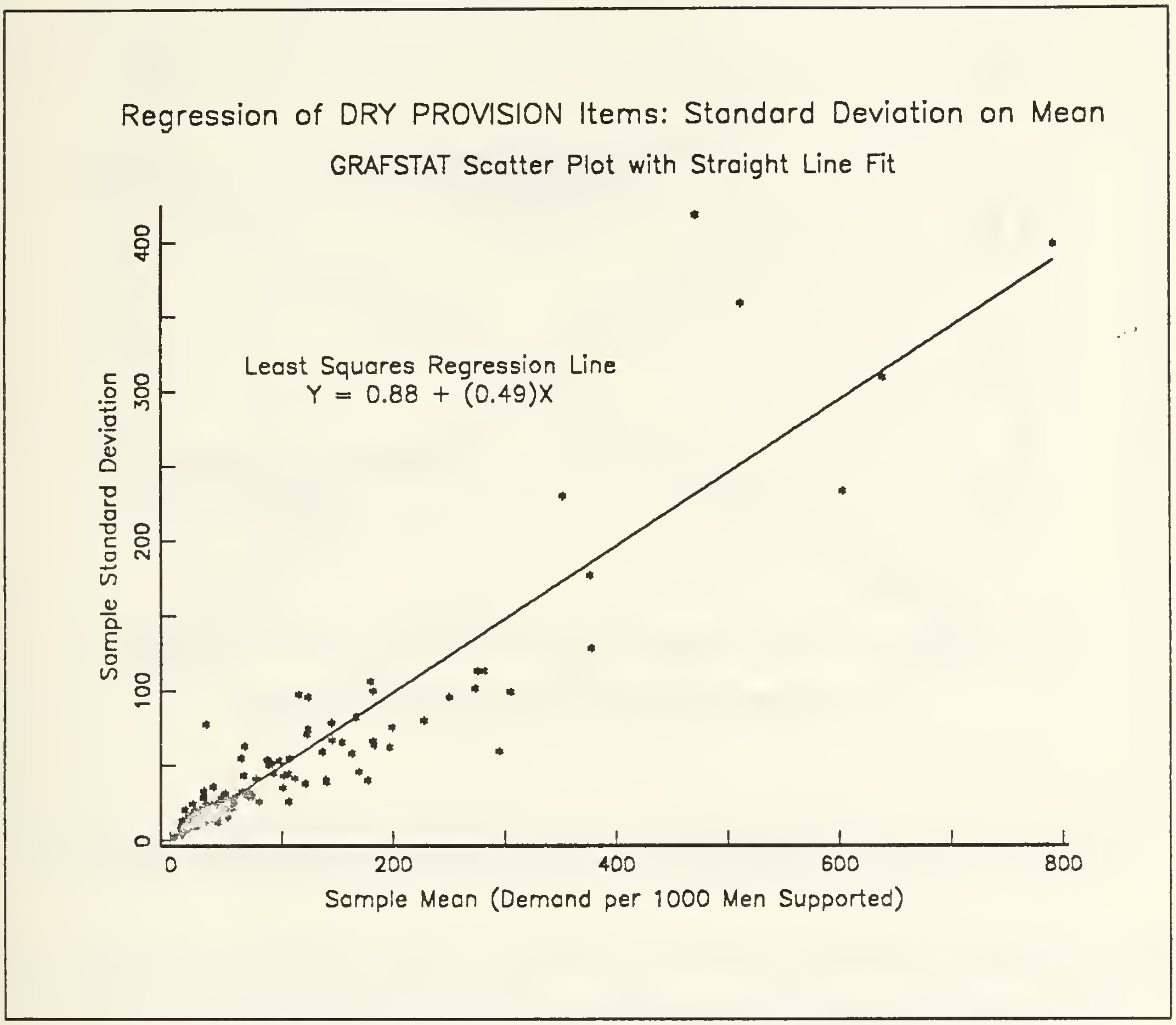

Figure 7. Regression of Standard Deviation on Mean for dry provisions

The slope of the regression line $\frac{\overline{\sigma}}{\overline{\mu}}$ yeilds the point estimate for $\hat{\sigma}$ equal to 0.464. With these values, the stocking objective for the Point Estimate Model becomes:

$$\text{Stocking Objective } = 2.93 \times AMD$$

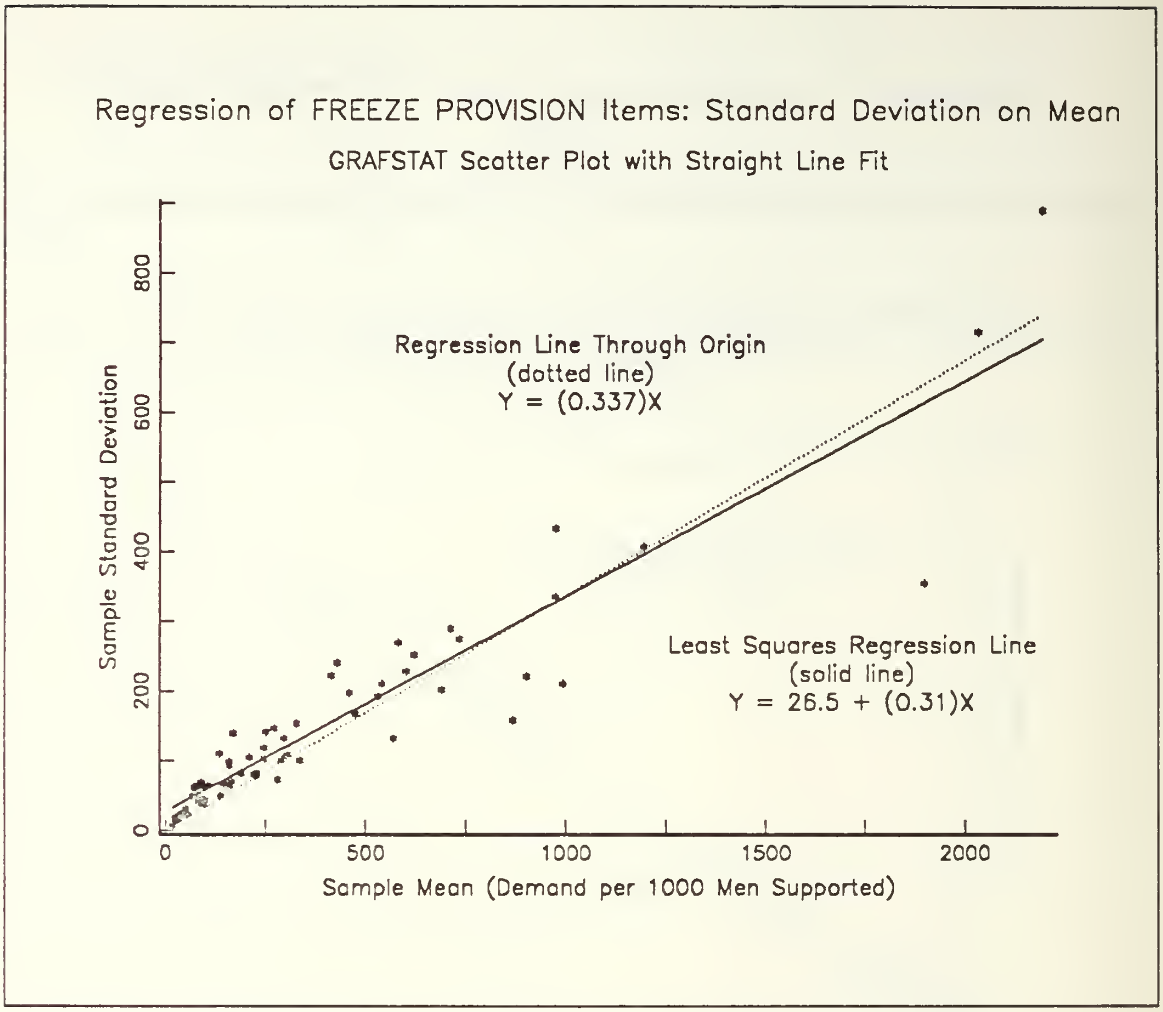

Figure 8. Regression of Standard Deviation on Mean for freeze provisions

The slope of the regression line $\frac{\overline{\sigma}}{\overline{\mu}}$ yeilds the point estimate for $\hat{\sigma}$ equal to 0.303. With these values, the stocking objective for the Point Estimate Model becomes:

$$\text{Stocking Objective } = 2.57 \times AMD$$

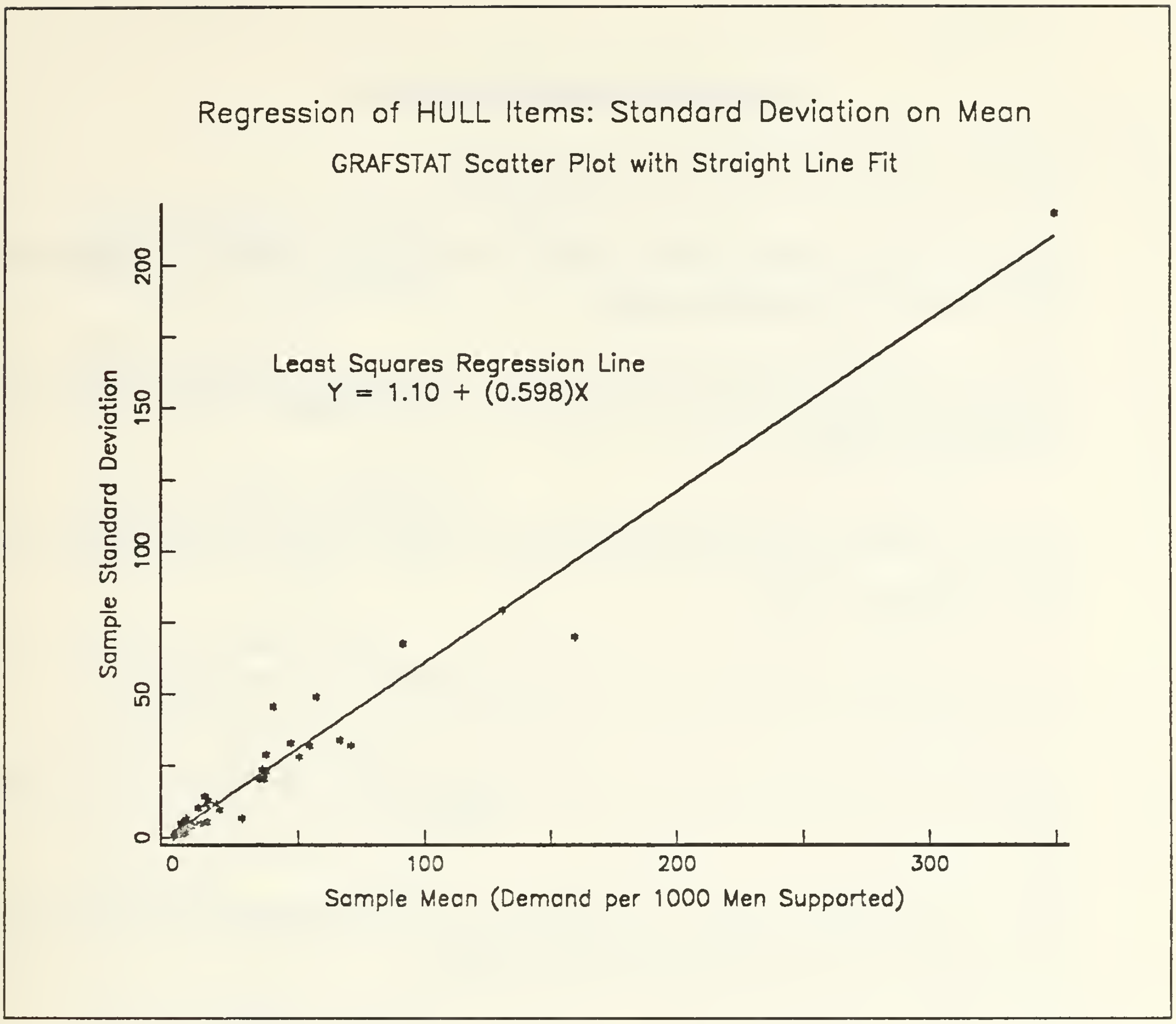

Figure 9. Regression of Standard Deviation on Mean for HULL items

The slope of the regression line $\frac{\overline{\sigma}}{\overline{\mu}}$ yeilds the point estimate for $\hat{\sigma}$ equal to 0.550. With these values, the stocking objective for the Point Estimate Model becomes:

$$\text{Stocking Objective } = 3.10 \times AMD$$

LIST OF REFERENCES

1. *COMNAVSURFLANT Notice 4423*, May 1988.

2. Sawyer, Mark A., *"Service Force Logistics in the Mediterranean," The Navy Supply Corps Newsletter*, March/April 1988.

3. Tersine, Richard J., *Materials Management and Inventory Systems*, New York: North Holland, 1980.

4. Prichard, James W. and Eagle, Robert H., *Modern Inventory Management*, John Wiley & Sons, Inc., 1965.

5. USNS SIRIUS (TAFS-8) *Message, DTG 282300ZMAR88*, March 1988.

6. Commander Service Force Sixth Fleet, *Message, DTG 151301ZMAR88*, March 1988.

7. Olkin, Ingram, Gleser, Leon J. and Derman, Cyrus, *Probability Models and Applications*, New York: Macmillan Publishing, 1980.

8. Duncan, Acheson J., *Quality Control and Industrial Statistics*, Homeland: Irwin, 1986.

9. USS SAN DIEGO (AFS-6), *Message, DTG 222111ZMAR88*, March 1988.

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